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Adaptive Autonomous Soaring of Multiple UAVs Using Simultaneous Perturbation Stochastic Approximation

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Abstract— **This paper presents a new algorithm for maximizing the flight duration of a single UAV (Uninhabited Air Vehicle) and UAVs group using the thermal model developed by Allen at NASA Dryden.**

As a first step, we suggest a new algorithm based on Simultaneous Perturbation Stochastic Approximation for quick and precise detection of the center of a thermal updraft where the vertical velocity of the air stream is the highest. The method takes into account the unstable behavior of the updraft dynamics and the drift of its center in time.

Then, a multi-agent system for joint flight of multiple UAVs is presented. A protocol for UAV communication providing effective information exchange on updrafts locations is proposed. A sufficient condition for the protocol to be effective is deduced theoretically. We show that the energy consumption of each UAV can be significantly reduced using the multi-agent approach.

I. INTRODUCTION

Large birds and glider pilots commonly use updrafts caused by convection in the lower atmosphere to extend flight duration, increase cross-country speed, improve range and conserve energy. UAV may also have the ability to exploit updrafts to improve performance. Results obtained in paper [1], [2], [3], [4] show that a UAV with nominal endurance of 2 hours can fly a maximum of 14 hours using updrafts during the summer and a maximum of 8 hours during the winter.

Extending the endurance of UAVs flight is currently an area of major research interest, because they are very popular for aircraft missions that would be dangerous or too boring for human pilots. And such missions as military surveillance or commercial usage as atmospheric satellites need extremely long endurance of UAV flight.

This paper is based on two key ideas for UAV soaring improvement. The first one is using simultaneous perturbation stochastic approximation method (SPSA) [5], [6], [7] for thermal updraft center detection. This method allows to treat the updrafts center drift effectively because of the tracking properties of SPSA shown in papers [8], [9]. It also helps to compensate the effect of horizontal wind considered as systematic noise as shown in work [10], [11].

The second idea is to use a group of UAVs instead of one unit for more effective location of updrafts and thus increasing average expected flight time for each UAV [12].

The multi-agent approach and the distributed decision making systems have become particularly popular because of their robustness and effectiveness when applied to problems with incomplete data solving. There are different approaches for gathering and processing information by autonomous agents. Each of them can only observe the environment partially and upload the observation data into a shared pool. All agents have their goals and values used in decision making. They have some beliefs and expectations regarding their complex surroundings that help them to define their behavior on each step.

Such distributed models are successful because there is no central control node with the major load on it. Each agent has its role that is changed with time. It helps to develop more flexible and fault-tolerant systems because of distributed data storage and traffic minimization between players.

Numerous frameworks for multi-agent cooperation have been developed recently and some simulations of multi-UAV cooperation have been made. Very significant results were obtained in Carnegie Melonie University where a group of UAVs flied together [13] in order to detect and destroy all RF emitters within a test area . Using Bayesian approach they built a distribution map of their expectations for each cell of the terrain. Then they corrected their paths in order to collect more information on unvisited regions and obtain the full picture of emitters locations. Similar results were obtained in the task of weapons detection by UAVs. The high potential of the multi-agent approach in tasks of this sort was proved in works both theoretically and by simulation results.

In our research a multi-agent system of UAVs was used for flight endurance maximization. Each UAV flies through its waypoints and gathers information on thermals location. A similar approach was studied in [14] for two UAVs. Due to the multi-agent approach all agents can obtain the whole picture of updrafts in the region quickly and correct their paths in order to pass through as many updrafts as possible. We also carried out a simulation to show the benefits of the multi-agent approach in this task. Increasing the UAVs number to three increases the flight duration of each UAV more than twice.

II. PROBLEM STATEMENT

A. Soaring of One UAV

The airplane we modeled was based on a small unmanned powered glider. The objective of our vehicle is to conserve battery energy and soar as long as possible over the test area. In our experiments the UAV uses a very simple strategy. It flies along a predefined path, measuring the vertical airspeed using the readings of an onboard GPS module. Thermal updrafts are identified as areas with positive airspeed values. The UAV should locate thermal updrafts within its flight path

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and use them to gain altitude. After climbing to the maximum available altitude it should return to its course and use the energy obtained by switching to soaring mode, i. e. keep its engine off, gliding.

It is known from observations that the maximum vertical speed in the updraft can be found in its center, while the edges remain relatively still. In fact, the vertical speed on the outskirts of the updraft is usually negative due to the fact the air is circulating inside the updraft. It is therefore vital for the UAV to detect the updraft center as quick as possible in order to benefit from its energy.

So, the first problem we tried to solve is the detection of the center of a thermal. Methods already used for this purpose usually give inaccurate results. They also either do not take into account the drift of the updraft's center in time and horizontal wind influence on the calculations or use very complicated models for this purpose.

$Constraints$:

It is absolutely necessary for the UAV to be able to glide with minimal altitude loss, in order to use the potential energy efficiently.

The soaring flight can only take place during daytime and the UAV path may not cross large water basins, as updrafts do not form neither above water, nor during the dark time.

We assume that the vehicle uses an onboard GPS receiver to calculate its vertical velocity in each point.

It is known that thermal updrafts often end with clouds on their tops. The wind conditions inside the clouds are known to be extremely severe, with rapid upward and downward streams. Entering the clouds level will usually result in a loss of the UAV. We therefore consider that there is an algorithm that allows the UAV to detect the top of the updraft and prevent it from entering the clouds.

B. Soaring of a Group of UAVs

A group of UAVs is flying over the test area as long as possible. They should therefore maximize their soaring time and effectively locate thermals within the field. They communicate each with other and exchange information on their locations and vertical velocity in this point. After each vehicle receives information on a newly detected updraft it has to decide between two behaviors: flying further along the predefined path or flying to the newly found updraft. The decision each UAV makes relies on its current altitude and an estimation of its energy balance. If the thermal found is too far from the UAV's current location it will not fly to it as more energy is likely to be consumed while approaching the updraft than energy that can be gained from it.

$Constraints$:

We assume that there exists a path planning algorithm that keeps the vehicles from colliding each with other. There are numerous methods that allow to generate paths for multiple UAVs in real time, from starting locations to goal locations in the presents obstacles of different sorts. A convenient solution was presented in paper [15] where the RRT-based planning algorithm was considered.

The distance between the vehicles is maintained according to a previously known average diameter of thermal updrafts at this time of year, time of day and geographic location and according to the units' radio range to assure they would be able to communicate.

III. SPSA Based Solution

Our algorithm discretizes the flying area into 10-meter square cells. The expected vertical velocity in each cell is initially set to a random negative or very small positive integer value. The UAV can sense its own vertical velocity in each cell. Each airplane knows its altitude in the current moment and can therefore decide whether it is necessary to seek an updraft to climb. We introduce an altitude threshold above which the UAV will not run the algorithm of thermal center location. Upon detecting a cell with vertical velocity value above a fixed threshold and provided the unit altitude is below the altitude threshold, the UAV will start the SPSA algorithm with 2-dimensional vector (x, y) and velocity value as profit function.

In our model we assume that updraft has Gausian velocity distribution. In the updraft center the velocity reaches its highest value. Thus, in order to use the energy of the updraft effectively we need an algorithm capable of detecting the maximum value of a function in a very noisy environment. Under these conditions we are facing a classical optimization problem.

The main assumption of the experiment was that stochastic gradient-free optimization methods are effective approaches for updraft center detection. Optimization methods are usually reduced to iterative alteration of some adjustable parameters from some initial guess (or a set of guesses) to a value that offers an improvement in the objective function. Let us consider a very simple case with only two optimization parameters which is suitable for our problem and with x and y coordinates and velocity function that depend on them. Maximization of the velocity function is the iterative process of coordinates adjustment SPSA presents a recursive optimization algorithm that does not depend on direct gradient information or measurements. This algorithm is based on an approximation of the gradient formed from (generally noisy) measurements of the objective function. Detailed description of SPSA can be found in the book [10], [16] or on http://www.jhuapl.edu/SPSA/. The algorithm starts with an initial "guess" at a solution, and this estimated solution is updated on an iteration-by-iteration basis with the aim of improving the performance measure (objective function).

The following step-by-step summary shows how SPSA iteratively produces a sequence of updraft center estimates.

Step 1: Initialization and coefficient selection. Set counter index $k = 1$. Pick initial guess and non-negative coefficients a, b and c which are heuristically chosen values in the SPSA gain sequences $a_k = a/k$ and $c_k = b + c/\sqrt{k}$. The initial guess in our implementation of the algorithm is the point where a positive updraft was first measured.

Step 2: Generation of the simultaneous perturbation vector. Generate by Monte Carlo a 2-dimensional random perturbation vector Δ_k, where x and y components of Δ_k are independently generated from a zero mean probability distribution satisfying the preceding conditions. A common choice for each component of Δ_k is to use a Bernoulli ± 1 distribution with probability of $1/2$ for each ± 1 outcome.

Step 3: Proceeding to the new waypoints. Proceed to next two points (x_k^+, y_k^+) and (x_k^-, y_k^-):

$$(x_k^{\pm}, y_k^{\pm}) = (x_k, y_k) \pm c_k \Delta_k.$$

Step 4: Velocity function evaluations. Obtain two measurements of the velocity matrix $w(x, y)$: $w_k^{\pm} = w(x_k^{\pm}, y_k^{\pm})$

Step 5: Quasigradient calculation. Calculate the quasi-gradient:

$$\hat{g} = \Delta_k \frac{w_k^+ - w_k^-}{c_k}$$

Step 6: Updating center estimation. Use the standard stochastic approximation form

$$(x_{k+1}, y_{k+1}) = (x_k, y_k) + a_k \hat{g}$$

to update the current center estimation.

Step 7: Iteration or termination. Return to Step 2 with $k+1$ replacing k. Terminate the algorithm if there is little change in estimations obtained on several successive iterations or the maximum allowed number of iterations has been reached.

Step 8: Climbing in the updraft. Circle around estimated updraft center in order to climb.

This method provides good approximation of the updraft center using a small number of measurements and no apriori knowledge on updraft location. Once a center of the updraft was encountered, a 30 sec. time penalty was put on the simulation to account the time that an actual vehicle would spend engaging an updraft and increasing velocity climbing around the center.

IV. Multi UAVs Solution

Consider a group of UAVs flying over a test area. The main objective of the mission is to maximize soaring time. The algorithm of battery power usage was designed to turn off power and begin soaring when the vertical velocity is above the threshold. So, each vehicle switches the soaring mode on and off depending on atmospheric conditions. When one agent detects an updraft it launches the updraft center location algorithm and sends a message containing information on its location, the estimated center of the updraft, the estimated velocity and the expected maximum altitude of the thermal to other agents. The other agents receive this message and choose the best strategy for them.

They estimate how much energy they will lose in the flight to the updraft and compare this value with the estimated energy gain from the updraft. If they can benefit from this updraft they shift their next waypoint to the center of the thermal, otherwise the UAVs continue their normal flight.

So, let us describe two algorithms used to model the UAVs behavior and communication.

Algorithm 1 Updraft detection and notification

```
loop
  if altitude is above safety threshold then
    switch engine off and soar along the flight path;
  else
    switch engine on and fly along the flight path;
  end if
  if current altitude is below the maximum altitude threshold then
    if current measured vertical velocity is above the
    updraft trigger velocity then
      run the SPSA-based center detection algorithm;
      send a broadcast message containing the current
      location, the estimated updraft center and the vertical velocity in it;
    else
      if received a message with updraft coordinates
      from another unit then
        run Algorithm 2;
      end if
    end if
  end if
end loop
```

The vertical velocity in the updraft center can be estimated by a simulation suggested in work [1]. Using measurements obtained by the UAV in its current location and some knowledge on the structure of an updraft it is possible to estimate the diameter of the updraft and the velocity distribution in it.

As it was described in the work [1] the convective-layer thickness, H, is the maximum height-above-ground that updrafts generally obtain. The mixing layer thickness was calculated using predawn rawinsonde balloon data and measured surface temperatures. Maximum velocity value in updraft reaches on the height $0.25H$. The expected altitude gain of the UAV could be found as difference of $gain = 0.7H - h$, where h is assumed as the current UAV altitude. All values are some heuristics derived from experiment.

Algorithm 2 Processing of the received signal and decision making

```
Calculate the distance between current location and the
center of the updraft;
Estimate the altitude sink if we proceed to the located
updraft center with engine off;
if the value obtained on step 2 is above the gain value
then
  Stick to current path
else
  Proceed to the updraft
end if
```

This simple method allows the UAVs to make effective decisions during their flight. On one hand, they fly rather close to each other and can benefit from updrafts detected by other UAVs, but on the other hand, they always correct their paths to avoid getting too close each to the other, thus being able to discover distinct updrafts in the test area. The optimal distance between the UAVs is calculated heuristically based on average updraft diameter in this day time and geographic location.

Let us show mathematically the advantage of multi-UAV soaring. Consider a group of K UAVs flying in an area with size S, in which n thermal updrafts of mean radius r are uniformly distributed. Suppose that the UAVs are flying along straight line parallel paths with mean distance of L between them and $L \leq 2r$. It will guarantee that any updraft situated between neighbor paths will be found by the group. Should any of the machines locate an updraft, the other UAVs will fly to the updraft location, climb and return to their paths. Note, that for the ease of the following proof, all the vehicles always proceed to the newly located updraft, unlike in Algorithm 3. For the matter of the following reasoning let us also consider the probability of a simultaneous detection of distinct updrafts by two or more vehicles of the group negligible.

Theorem 1. *Let c designate the energy sink rate for a single UAV flying at the cruise speed and b — the energy benefit obtained from using the thermal updraft. It is sufficient for the multi-UAV strategy to be efficient (the expectation of total energy consumption for each UAV is minimized by this strategy) that the following equation is held:*

$$L = \frac{b}{2c(K-1)}. \tag{1}$$

Proof. Let p_1 be the mathematical expectation of the number of updrafts located by a single vehicle over a straight line path of length l.

$$p_1 = \frac{2rln}{S}$$

It is actually the probability of the updraft center being in a rectangle whose area is $2rl$ multiplied by the total number of thermals within the field. This is, in fact, a lower bound estimation, that does not put any restrictions on the location of updrafts and the distance between them.

Let us introduce the expectation of energy consumption by a single UAV:

$$E_{single} = lc - p_1 b = l\left(c - 2rb\frac{n}{S}\right).$$

Similarly, we can obtain the expectation of the number of updrafts located for the group of K UAVs which are flying along straight line parallel paths with mean distance of L between them.

$$p_K = \frac{(2r + L(K-1))ln}{S}$$

Taking into account that the mean distance from an UAV to the found updraft is equal to $L(K-1)/2$, we can derive for the mean energy consumption when using the multi-agent strategy.

$$E_{multi} = lc - p_1 b - (p_K - p_1)\left(b - 2\frac{L(K-1)}{2}c\right) =$$

$$= l\left(c - [2rb + L(K-1)(b - L(K-1)c)]\frac{n}{S}\right).$$

The first part of the expression is similar to the single UAV case. The second part is the energy benefit obtained from the updrafts located by the $(K-1)$ fellow vehicles minus the energy penalty for flying to the location of the updraft.

Minimizing the last formula by L we derive (1) and the difference between energy consumption expectation when using the single UAV and the optimal multi-UAV strategies, which is:

$$E_{multi} - E_{single} = -\frac{ln}{S}\frac{b^2}{2c}.$$

The expectation of energy consumption when using the multi-UAV strategy is, therefore, lower. □

In the above reasoning we assumed the distance between neighbor paths remains constant throughout the whole mission. In practice, however, the distance might and should be adapted according to observations of mean thermal diameter, mean distance between thermals and other atmospheric conditions, such as horizontal wind speed.

V. Simulation Results

For this project, we chose to use a thermal updraft model developed by Allen at NASA Dryden (Ref. [1]) for a similar autonomous UAV soaring project. This model was developed using atmospheric data collected by NOAA in Nevada using rawinsonde balloons released every 12 hours over the course of a year.

We used Allen's model to create a dynamic field of thermal updrafts within the specified test area, that the UAV was constrained to fly in. Updraft positions were randomly chosen and held for 20 min at a time. The 20-min thermal lifespan was chosen from estimates given in [17] and from personal observation of cumulus clouds. As updrafts have finite lifetime, the value function estimate of particular visited cell becomes less and less accurate depending on how recently the UAV has visited it. To reflect this increasing uncertainty with time, a discount factor 0.95 was applied at each time step such that the estimated velocity of each cell gradually decays toward zero. Fig. 1 shows an example of such a field at a particular time during the simulation:

TABLE I

RESULTS OF SPSA

x, Average velocity value in the point where spsa was initiated	p, Average velocity in the updraft center as found by SPSA
0.55	1.9
0.74	2.65
0.55	2.29
0.65	2.43

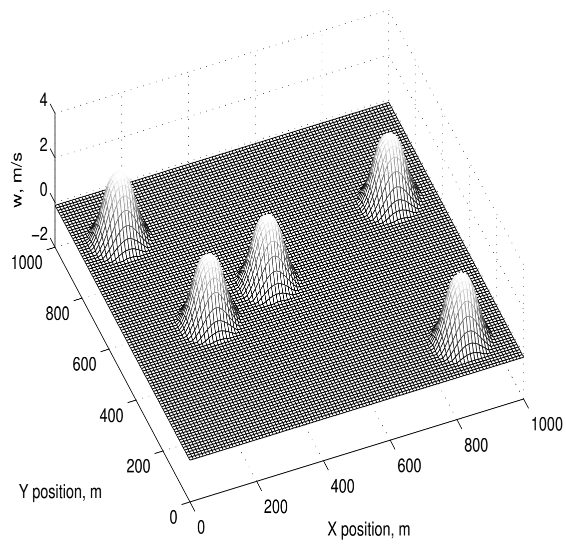

Fig. 1. Sample thermal updraft field.

A. Soaring of One UAV

In our experiment the UAV flies through randomly chosen waypoints. As the airplane flies it tries to detect the updrafts its path coincides with. When the vehicle finds any points with positive vertical velocity and provided its altitude is less than a preset threshold it starts center detection algorithm to gain altitude using the upward directed vertical wind.

The summarized results of the experiment are tabulated in Table 1. In order to obtain these statistics we made 100 experiments with SPSA updraft center detection using only 10 measurements. The vertical velocity changes between -0.12 and 2.75 over the test field.

The results of a sample experiment are also shown on Fig. 2 where the estimated updrafts center are the red circles.

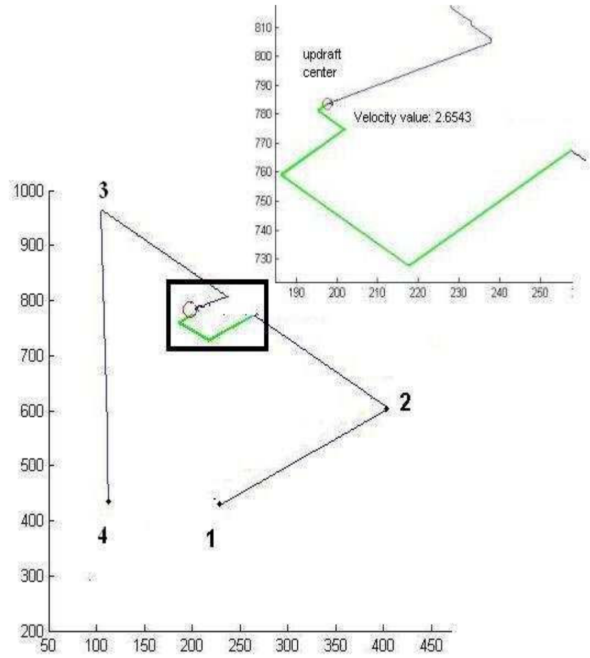

Fig. 2. Path with centers detection using SPSA.

B. Soaring of a Group UAVs

To demonstrate the effectiveness of our algorithm we made some simulations in which a group of UAVs is flying across a square test field. In the experiment all updrafts are placed randomly within the test area. Each UAV flies along a straight line and measures its vertical velocity using GPS in every cell. When it observes a cell with positive vertical velocity, the vehicle communicates with others UAVs and shares this information. As mentioned above, all the vehicles use Algorithm 3 that helps them to decide whether they should stick to their current path or rather approach the newly found updraft. A typical sample path obtained by this simulation is shown on Fig. 3. We assume that a collision avoidance algorithm is employed when the vehicles proceed to the updraft location.

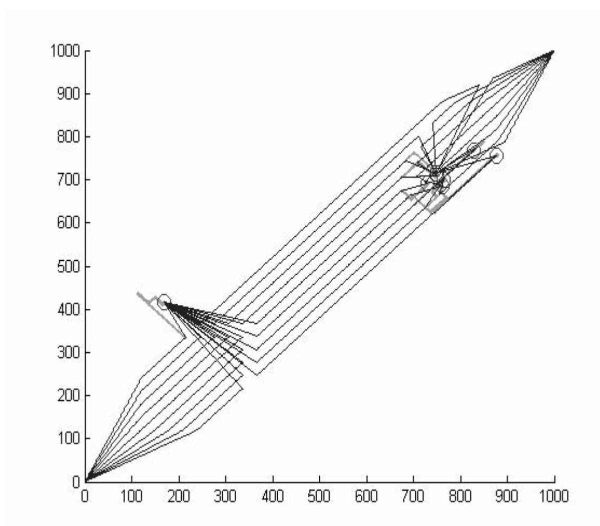

Fig. 3. Multi-UAV Soaring ($K = 9$).

We also carried out a simulation using the Monte-Carlo method performing 100 iterations with variable number of UAVs in order to show the relation between energy sink rate and the number of UAVs. We consider that the power sink rate for vehicle flying at its cruise speed, without using thermal updrafts is 100 units per 1000 distance units. The results of the simulation are shown on Fig. 4.

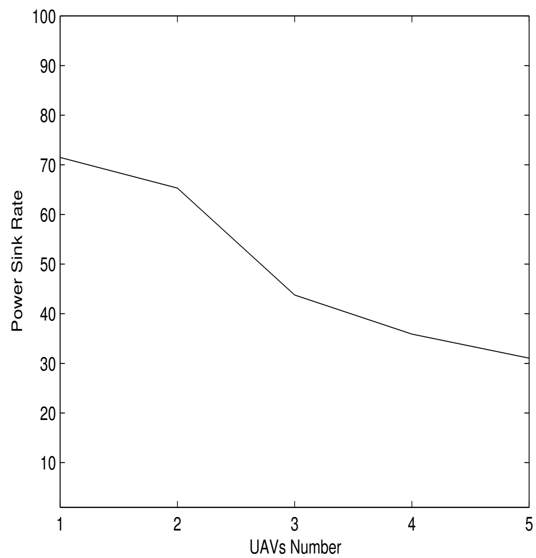

Fig. 4. Power Sink Rate for Variable Number of UAVs

It is clearly visible from the diagram that the power sink rate decreases as the the number of UAVs in the party grows. The sink rate for a single vehicle in a group of five UAVs is as low as 30, which is about a half of the sink rate for single UAV soaring.

VI. Conclusion

In our work we have demonstrated a quick and accurate method of locating the center of a thermal updraft. The method proposed does not require any apriori information on the number and the location of thermals in the test area. In contrary to the online machine learning method proposed in [18] our algorithm allows locating updrafts “on the fly”, without need in additional passes to collect more data.

We have also considered the expansion of the algorithm for using it with multiple vehicles. We showed theoretically the sufficient condition for the multi-UAV soaring to be effective. It was shown using simulation that the multiagent approach can be exploited to increase the effectiveness of updrafts location, thus increasing the overall airborne time for the whole party.

It is obvious, however, that the operation of UAV groups becomes complicated as the number of UAVs grows, the benefit of more effective updraft detection thus becoming less noticeable. The general approach proposed is therefore that the number of UAVs should be reasonably increased in tasks involving long-range operation, while remaining low enough for the group to be still efficient.

VII. Future work and Acknowledgements

Several directions are open for future work on the subjects that this project explored. For more realistic simulations we need to increase the complexity of the thermal and aircraft dynamics models. We also plan to test our algorithms on a real UAV platform, using the Java JADE framework for implementing the multi-agent cooperation.

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