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The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides

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ABSTRACT

The application of pesticides and fertilizers in agricultural areas is of crucial importance for crop yields. The use of aircrafts is becoming increasingly common in carrying out this task mainly because of their speed and effectiveness in the spraying operation. However, some factors may reduce the yield, or even cause damage (e.g., crop areas not covered in the spraying process, overlapping spraying of crop areas, applying pesticides on the outer edge of the crop). Weather conditions, such as the intensity and direction of the wind while spraying, add further complexity to the problem of maintaining control. In this paper, we describe an architecture to address the problem of self-adjustment of the UAV routes when spraying chemicals in a crop field. We propose and evaluate an algorithm to adjust the UAV route to changes in wind intensity and direction. The algorithm to adapt the path runs in the UAV and its input is the feedback obtained from the wireless sensor network (WSN) deployed in the crop field. Moreover, we evaluate the impact of the number of communication messages between the UAV and the WSN. The results show that the use of the feedback information from the sensors to make adjustments to the routes could significantly reduce the waste of pesticides and fertilizers.

1. Introduction

Unmanned aerial vehicles (UAVs) have become cheaper because many control functions can now be implemented in software rather than having to depend on expensive hardware. This has allowed single or multiple UAVs to be employed for real-world applications. The UAVs very often require a means of communication so that they can communicate with on-land computers, sensors or other UAVs. As most of the research with UAVs is still in its initial stages, there are a number of open questions that need solving, like mapping and localization schemes [33], route planning [29], coordination and task allocation [30,28] and communication issues [6], among others.

In this paper, we propose an architecture based on unmanned aerial vehicles that can be employed to implement a control loop for agricultural applications where UAVs are responsible for spraying chemicals on crops. The process of applying the chemicals is controlled by means of the feedback from the wireless sensor network which is deployed at ground level on the crop field. Furthermore, we evaluate an algorithm to adjust the UAV route to changes in the wind (intensity and direction) and the impact caused by the number of messages exchanged between the UAV and the WSN. The information retrieved by the WSN allows the UAV to confine its spraying of chemicals to strictly designated areas. Since there are sudden and frequent changes in environmental conditions, the control loop must be able to react as quickly as possible.

The information retrieved by means of the WSN provides the UAV with knowledge of the position and amount of chemicals detected by every sensor of the crop field. However, after the application of the chemicals by the UAV, some areas of the crop may not have a sufficient amount of chemicals; the reason for this is the high speed of the UAV and even though the controls allow the UAV to adjust to sudden random changes of wind as quickly as

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possible, this might not be enough to maintain a perfect lane. As a result, what happens is that we might have some clusters without the correct amount of chemicals being dispersed. Hence, in this paper we also show how to build a chemical concentration map using the data provided by the WSN. The purpose of this is to show clusters where there is an insufficient application of chemicals and the map might be used to perform new UAV applications in designated areas. We show how to build these maps using Instance-Based Algorithms [2] and Density-Based Algorithms [20].

This paper is an extended version of a previous study [10]. It aims to describe the methodology that is employed in a more thorough way, conduct new experiments and discuss the new obtained results. Furthermore, we describe how a chemical concentration mapping can be carried out by using the data obtained from the WSN and we present evaluations with real hardware, where we measure the communication time between the UAV and a ground sensor employing XBee-PRO Series 2.

This paper is structured as follows: in Section 2 we discuss related work on mobile ad hoc network routing protocols and cooperative sensing. Section 3 outlines the proposed method, by describing the proposed system architecture and the details of its development. Section 4 describes the evaluation of all the conducted experiments, the first for the UAV route adjustment, the second for building the chemicals concentration maps (clusters) and the third for the evaluations employing real hardware. The final section concludes the paper and offers some future perspectives.

2. Related work

2.1. Routing protocols

Mobile ad hoc network (MANET) routing protocols can be divided into a few main groups: (i) flat proactive routing, (ii) on-demand reactive routing, (iii) hybrid schemes, (iv) geographical routing and (v) opportunistic routing. Proactive (table-driven) ad hoc routing protocols maintain their routing information independently of communication needs. Status update messages are sent periodically or when the network topology has changed. Thus, a source node gets a routing path immediately if it needs one. This results in low latency and makes them suitable for real-time traffic. When they use proactive routing protocols, nodes proactively update their network state and maintain a route regardless of whether data traffic exists or not. The main drawback of these routing protocols is the high overhead they need to keep the network topology information up-to-date. All the nodes require a consistent view of the network topology.

Reactive (on-demand) routing only establishes routes if they are required. This saves energy and bandwidth during periods of inactivity. It should be noted that a significant delay may occur as a result of the on-demand route discovery. Compared to proactive ad hoc routing protocols, one advantage of reactive routing protocols is the lower overhead control. Furthermore, reactive routing protocols have better scalability than proactive routing protocols in MANETs. One drawback is that reactive routing protocols may experience long delays for route discovery before they can forward a data packet. Reactive protocols perform well in light-load networks.

Geographical routing protocols assume that a source knows its position and can determine the position of the destination. Moreover, each node knows its neighbors' positions. In comparison with flooding-based approaches, geographical routing has a reduced overhead for route discovery. Geographical routing protocols only require neighbor information containing their location to route packets and do not need to maintain per-destination information. Most geographical routing protocols use greedy forwarding as the main method to select the next hop. In order to avoid dead-ends in the routing path, face-routing has been proposed to route around a void.

Opportunistic routing [7,35,27] assumes that an end-to-end communication path may frequently be disrupted or may not exist in a MANET at any time. The routing mechanism forwards the message towards the destination on a hop-by-hop basis and the next hops are selected according to protocol-specific characteristics. This means that it is not essential to have a stable end-to-end connection from the data source to the destination. The packets are forwarded even though the topology is continuously changing.

2.2. Cooperative sensing

Wireless Sensor Networks are networks composed of several wireless nodes. These nodes are often deployed near or inside environments or phenomena with the aim of sensing/obtaining information about it. The information is then routed to a command center, where the data can be examined and appropriate action can be taken [9]. According to [3], those nodes are small embedded systems with the three following components: (i) mote, that is the main component of the sensor node, it is able of communicate wirelessly and should be programmable. Traditionally they are composed of a microcontroller, a radio and an energy source; (ii) a set of sensors, whose objective is to sense the environment and collect data (i.e., temperature, humidity); and (iii) data interface, that can be a USB or a serial port, used to connect the mote to a computer so that it can be programmed. Some motes allow this by means of the wireless interface.

One major issue when dealing with WSN is the limited source of energy, which is normally provided by batteries. Although the batteries can be changed, this can be dangerous for human beings as the sensor nodes might be installed in hazardous environments (i.e., volcanoes, chemical/nuclear affected areas). Furthermore, changing batteries is expensive (and requires both human and financial resources). Some techniques can be employed to increase the lifetime of the nodes. The first of these is the on–off behavior, i.e., the sensor nodes turn off some components to save energy. The best component to turn off is the radio, because it is the component which uses most energy [24]. This procedure makes the sensor node unreachable for some time, so the communication protocols used by the WSN must be aware of it. The second technique seeks to enhance the lifetime of the WSN by using limited radios (low power and bandwidth) because it requires less energy. As a result, the nodes can only communicate with the nearest neighbors. Hence, to send any information from the WSN to a base-station, the message must be routed via several nodes. This method is called multi-hop communication.

The cooperation of several types of nodes in a WSN application, including static and mobile nodes, can be seen in the work by Erman et al. [14]. They have established a platform of heterogeneous wireless sensor nodes with the objective of sensing and monitoring fires in buildings. They propose to deploy nodes inside a building where each node is capable of detecting the temperature of the room. When a fire is detected by the WSN, an UAV is called to fly near the fire and to deploy more sensors, and thus gather more information. When the fire-fighters arrive in the building, they wear a so-called Body Area Network so that they can receive the information from the nodes and also collect information required for the protection of the fire-fighters, such as body temperature and concentration of CO_2 near their mask.

Another project that relies on the cooperation of different types of nodes can be seen in the work by Valente et al. [31], where it is proposed the deployment of sensors in several vineyards to collect information about factors such as temperature and humidity.

Initially, the collected data were routed to a command center, but as the vineyards are more than 70 m away from each other, they could not exchange the data. The authors tried to use more powerful radios, but this led to excessive battery consumption and the life-cycle of the WSN was drastically reduced. In light of this, the solution was to use an UAV to fly over the vineyards and gather data when the farmer needs it. Following this, the UAV comes back to the command center and the data is sent to a Graphical User Interface system where the farmer can visualize the information about the vineyards and determine the parameters of the watering system.

3. Our approach to spraying pesticides

3.1. UAVs for agricultural application

Fig. 1 shows the application scenario outlined in this paper. The current scenario has one UAV and *n* ground sensors. A UAV is used to spray chemicals on an agricultural field. However, the neighboring field, which may belong to another owner or be a protected area, must not be sprayed. Moreover, the UAV must keep to its lane of operation (i.e., within the boundary). If the UAV used for spraying comes too close to the neighboring field, or if there is a sudden change in the direction of the wind, the chemicals might fall on the neighboring field and this must be avoided. We propose that the UAV gets information from the WSN deployed in the crop field so that it is able to make the necessary adjustment to the trajectory. If a sensor detects an excessive concentration of chemicals, the UAV doing the spraying will be guided away from the border.

The proposed algorithm to adjust the UAV route can be understood with the aid of Fig. 2. Periodically, the UAV broadcasts messages to the sensors in the field to determine the amount of chemicals being perceived. If the sensor receives the message, it responds with a message reporting the amount of measured chemicals and its position. On the basis of this information, the UAV can make a decision about whether to change its route or not. The route is changed when the amount of chemicals perceived by the sensor does not match that of the proposed threshold (each type of chemical must have its own threshold).

An algorithm that requires the sensor nodes to be distributed in the form of a matrix is used to improve the application of the pesticides during the spraying. Fig. 2 shows the flowchart with the rules for changing the route; (1) Periodically, the algorithm sends a message to make queries to the sensor nodes which are scattered on the field. The sensor nodes located at the previous position of the UAV respond to this message with information about the amount of pesticides. (2) With this information, the UAV calculates the difference in the concentration of pesticides between each sensor node (left and right). (3) If the difference is greater than a predefined threshold, the algorithm calculates the route change, otherwise it continues in the pre-defined route and waits for the next query. This threshold may be different for each type of

Fig. 1. Sample of application scenario.

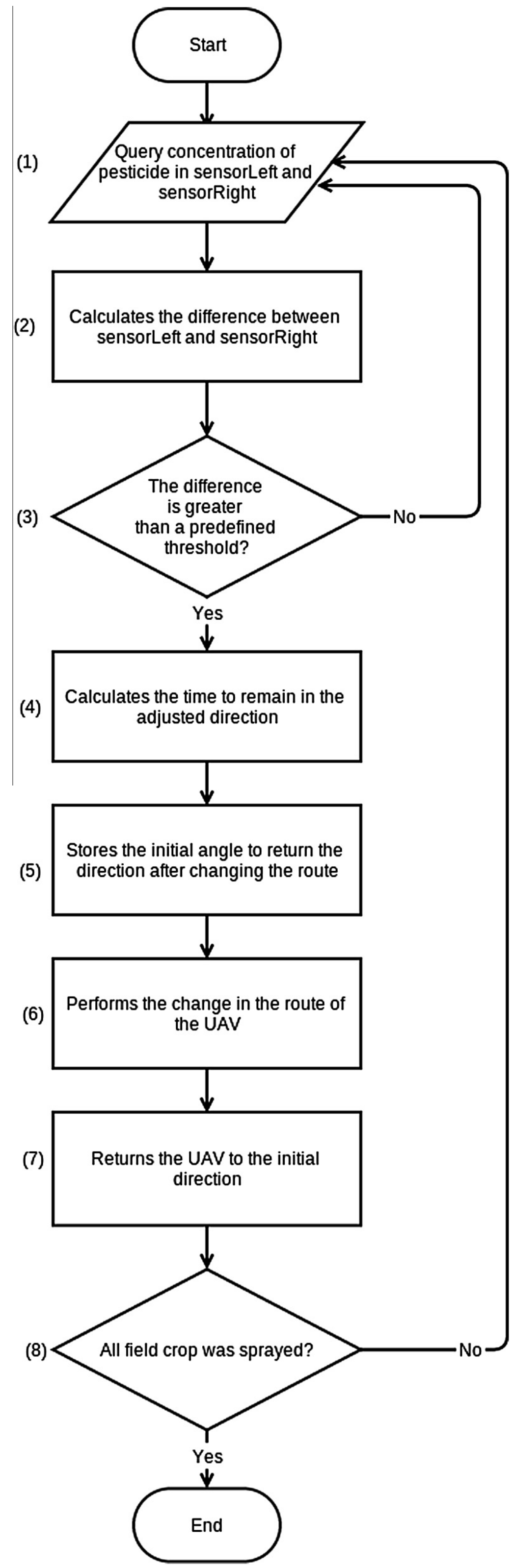

Fig. 2. Flowchart showing the rules for changing the UAV route.

pesticide, so it should be predefined. (4) The dynamics of this solution are revealed by calculating the time that the UAV remains with the changed route before returning to the initial path of the UAV. This computation is based on the difference between the samples and the change in the predefined factors (along with the threshold). (5) The track angle of the initial direction is stored and (6) a trajectory change is performed by the algorithm. The route change consists of turning the UAV at an track angle of 45 degrees to the side where there is less concentration of pesticide. (7) At the end of the predetermined time required for the algorithm to change the route, the algorithm returns to the start track angle. (8) If the spraying of the field crop has been completed, the algorithm ends, otherwise it returns to the query sensor nodes. The algorithm that corresponds to the flowchart can be seen in Algorithm 1. In the algorithm, θ was set to 45 degrees and the *durationTime* that is employed to calculate the time to remain in the new route was equal to 4.0. These values were obtained empirically. It is worth to emphasize that this occurs inside a loop, so, for each query it will maintain the new route for the predefined time. Terrain and environmental configurations are described in Section 4.

Algorithm 1. Adjusting the UAV route

```
diff ← sensorLeft − sensorRight;              // see Figs. 2(1) and (2)
if (abs (diff) > threshold) then              // see Fig. 2(3)
    duration ← abs (diff) ÷ durationFactor;   // see Fig. 2(4)
    initialAngle ← angle;                     // see Fig. 2(5)
    if (diff < 0) then                        // see Figs. 2(6) and (7)
        setAngle (angle + θ);
    else
        setAngle (angle − θ);
    scheduleChangeRoute (angle, duration);
```

The algorithm used to adjust the UAV route is based on control theory, that is, the data collected by the ground nodes are used as inputs of a control system, and the output is the track angle which the UAV must take. The system has two inputs, one of which is the chemical concentration perceived at the right-hand side of the plane and the other is the chemical concentration perceived on the left. The system calculates the time the UAV will spend in the new route before returning to the pre-defined route, and attempts to correct the amount of chemicals sprayed by adjusting the track angle of the UAV flight. The algorithm decides the new route on the basis of the data collected by the UAV from the ground nodes.

3.2. System development

There are two main ways to validate large-scale WSN projects: testbeds and simulations [8]. The testbed approach involves a small version of the project, where the system is usually split into modules, each of which is tested separately. The use of a testbed approach has some drawbacks since it is hard to validate the system in a real environment. In addition, Wireless Sensor Networks are faced with other problems that are not found in traditional networks. For example, while the tests are being conducted, the nodes constantly have to store debug messages or even exchange debug messages. This can cause some problems, e.g., the interference of multiple debug messages, or high memory usage, or even battery exhaustion [8]. As a result, the WSN community has been attempting to validate the first stage of a project by adopting a simulation approach [14].

There are several network simulators available (e.g., ns2, JavaSim, SSFNet, Glomosim). However, most of these simulators were designed for specific networks and their usage for wireless network simulation is wide-ranging, and, sometimes, requires the implementation of wireless network protocols and algorithms [22]. In addition, in [22] it is possible to find out more about the features of these available simulators. In carrying out this project, the simulator that is being used is OMNeT++.[1]

The OMNeT++ simulator is a discrete event simulator, based on C++ to model communication networks, multiprocessors and other parallel and distributed systems. This simulator is open-source and can be used for academic, educational and commercial purposes. It has been available for the Unix and Windows operating systems since 1997 [32]. This simulator was not designed to work within a specific network, and as a result, it is used in several kinds of simulations, such as networks with queues, wireless networks and P2P networks [34]. Owing to its generic design, OMNeT++ has a number of frameworks that have been established for specific networks, such as MiXiM,[2] a framework for wireless network modeling. This framework provides detailed models of wireless channels (e.g., fading), wireless connections, models for mobility, models for obstacles and several communication protocols, especially for the MAC layer [19].

There are several systems that can be used to build autonomous helicopters for agricultural applications. Currently, the most promising one, is the Yamaha RMAX, which is designed for agricultural uses, include spraying, seeding, remote sensing and precision agriculture. This includes a liquid sprayer with a tank capacity of 8 litres (2 tanks) and a granular sprayer with a tank capacity of 13 litres (2 tanks). Complete specifications can be seen in [36]. However, the Yamaha RMAX is not fully autonomous yet, hence, studies that adopt intelligent and autonomous approaches are needed to develop new versions. Another technical strategy that can be adapted to autonomous helicopters for agricultural applications, can be found in the work by Huang et al. [18], which examines the deployment of a spraying system for the Rotomotion UAV SR200 [25]. The Rotomotion UAV SR200 has up to 20 kg of payload capacity, although it does not have a spraying system off the shelf. In their work, the requirement was to spray 14 ha of land with a single load, at a low volume spray rate (0.3 L/ha). Hence, 4.2 L of chemical was needed to cover the 14 ha of land.

Furthermore, Ehmke [13] has written a featured research paper in which he describes several aspects of the task of employing unmanned aerial systems in agricultural fields, such as the necessary skills, the costs involved and the privacy policy that is entailed in the crop scouting and mapping by UAVs. As our aim is to study the behavior of the UAV, in our approach, both of the above-cited UAVs can be employed. Naturally, there must be a fine-tuning phase involving the parameters of the algorithm, due to the mechanical characteristics of each UAV. Furthermore, this fine-tuning phase should also take into account the type of crop being handled (soy, rice, corn, grapes, sugarcane) and the type of pesticide to be used.

3.3. Implementation details

The system implementation (currently in a simulation model) has been divided into two modules: (i) the *Behavioral Module* and (ii) the *Chemical Dispersion Module*. In the *Behavioral Module* we simulate the communication between the WSN positioned in the field and the UAV, using OMNeT++ with the MiXiM framework. The *Dispersion Module* was developed by means of Python[3] and SDL[4] library. The two modules run simultaneously, in an integrated way[5] with socket-based communication. The *Behavioral Module* sends the current position of the UAV (x, y, z) to the *Dispersion Module* along with the track angle and speed of the UAV (θ, v). Furthermore, the wind modeling is carried out in the *Behavioral Module*; this emulates changes in wind direction and speed and provides information to the *Dispersion Module* about changes in the environment. Fig. 3 shows an example of a sequence of scenes with the communication between UAV and WSN. In this example, there are 12 nodes representing the sensors in the field and one node representing the UAV.

The *Dispersion Module* calculates the fall of the chemicals, by obtaining the position and fall time of each drop. The WSN, in turn, determines the amount and position of the chemicals and returns this information to the *Behavioral Module*. Periodically, the UAV sends a broadcast message to the ground sensor nodes, requesting the concentration in its area. The ground sensor nodes that receive this message, connect to the *Dispersion Module* and request its concentration using their positions (x, y, z) as parameters. In this way, they can respond by giving details of the concentration in this area to the UAV. By means of these response messages from the ground nodes, the UAV can call a decision manager, for instance, to compute its decision and then change its route if necessary. The chemical dispersion is based on a simplified pollutant model, which considers (1) the vector of the initial velocity of the particle when it is sprayed, (2) the vector of wind speed and (3) gravity. The interactions occur until the particles hit the ground. Nonetheless, in conducting a simulation of how chemical falls, we must not only take account of the height of the UAV, factors like wind speed and direction, temperature, humidity and the droplet size also influences the dispersion, as can be seen in the works by [5,11,16,12]. However, as we are working to achieve a path optimization that can reduce the waste of chemicals, we believe the simulation is satisfactory at this stage. After having a real spraying mechanism, we believe we will be in a position to fine-tune some of the current parameters of the algorithm that adjust the path of the UAV to particular environmental conditions, weather patterns and types of chemical droplets.

Fig. 4 shows the proposed system sequence diagram and we can see the relationship between the nodes. The first activity is wind management which sets the velocity and direction of the wind through the setWind (v, θ) function. This activity can occur at any time, by changing the wind properties in the *Dispersion Module*. After this, while the UAV is moving through the field, it can use the sprayChemicals function, and inform the *Dispersion Module* of its position (x, y, z), velocity and track angle. With this information, the *Dispersion Module* is able to calculate where the chemical particles are going to be sprayed.

Regarding the ideal type of UAV, it must have the following characteristics: (1) be capable of flying at $\approx$15 m/s, and (2) be equipped with a spray bar that can spray the pesticide. It might be an autonomous airplane or an autonomous helicopter, although in the real-world scenario we are working with helicopters, as can be seen in Fig. 9. With regard to the UAV flying pattern, a traditional technique is mimicked, in which the pilot performs the spraying in predefined tracks. The UAV flies from the beginning to the end of the track and across the field as many times as needed to cover all the tracks. However, in this work the results are based on flights along a single track. With regard to terrain characteristics, the simulation environment considers the sensors deployed as a matrix (this can be understood with the aid of Fig. 8a). It is expected to have random distributed sensors which will be a subject for future studies.

Currently there are some technologies that can identify chemical levels in the air, soil or water. These technologies can calculate the degree of moisture in terms of the percentage of a specific chemical composition in a given area. In addition to determining the degree of chemical concentration, the sensor nodes can be used

[1] OMNeT++ Network Simulation Framework, http://www.omnetpp.org.
[2] MiXiM project, http://mixim.sourceforge.net.
[3] Python Programming Language, http://www.python.org.
[4] Simple DirectMedia Layer, http://www.libsdl.org.
[5] Simulation video available at http://youtu.be/4wFJZZEYAKM.

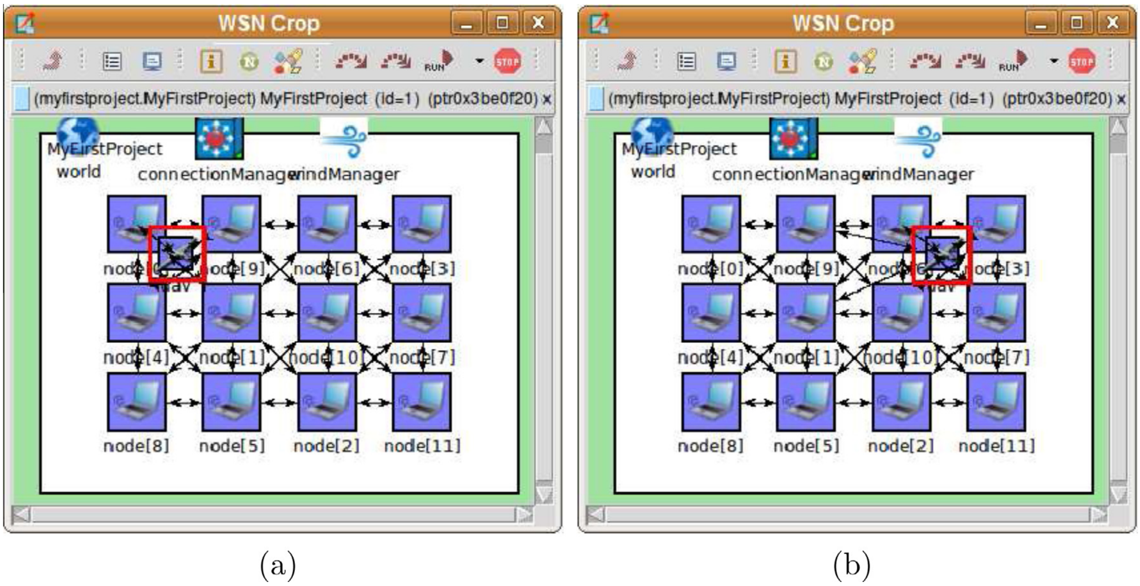

Fig. 3. OMNeT++ project. Figures show the sequence of scenes with the communication between UAV and WSN. The red blocks present the UAV and the arrows present the communication capabilities.

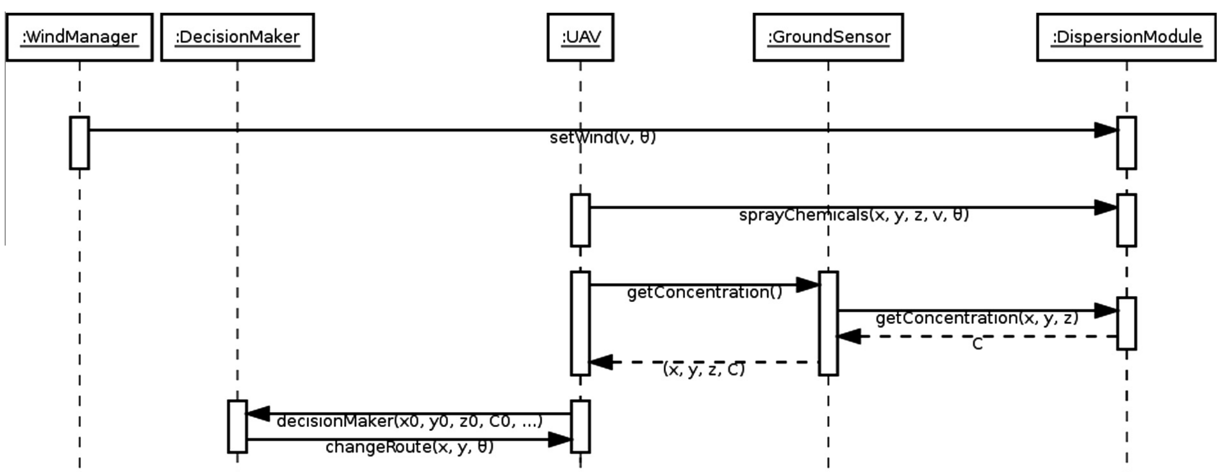

Fig. 4. Sequence diagram of the proposed model.

to detect diseases in plants or insect infestation [17,26,21]. In the current version of this work, we have employed simulated sensors. The use of real electrochemical sensors is also a subject for future work.

We are planning to have a network of UAVs (swarm) and also a network of several sensors (which are currently being simulated). The use of correct routing protocols is very important to minimize battery consumption and maximize communication capabilities, which have to be fine tuned to the specific environment. We have been carrying out an investigation of several routing protocols, as this is a part of the project; however, for the current version, there is only direct communication between the sensor nodes and the UAV.

4. Evaluations and results

4.1. Adjusting the UAV route

In evaluating the algorithm to adjust the route for the UAV, we used a wind dataset with data that included wind direction and intensity. With this dataset in hand, we were able to ensure a better area of coverage even in changeable weather conditions. In the evaluation, the UAV was programmed to fly over the crop while spraying chemicals. Moreover, we tried to evaluate whether the number of message exchanges between the UAV and the WSN improved the system performance or not. The set of parameters included in this evaluation can be seen in Table 1.

In this set of evaluations, we carried out experiments including changes in the type of wind, changes in the number of messages between the WSN and the UAV and experiments to point out the behavior of the system while using the proposed algorithm. We performed these 70 times for each parameter set, with different random seeds. Fig. 5 shows the results of these experiments. It should be emphasized that we established an area of 1100 m by 100 m as the size of the simulated crop field. In addition, we only selected a section of the above-mentioned area as the part to be sprayed (i.e., 1000 m by 50 m). The number of sensors inside the crop field is 22 and the UAV velocity and operating height is 15 m/s and 20 m, respectively. We define light wind as 10 km/h and moderate wind as 20 km/h.

We can see in Fig. 5 that the best results are CL10 and RL10. This makes sense since both CL10 and RL10 are the evaluations that rely

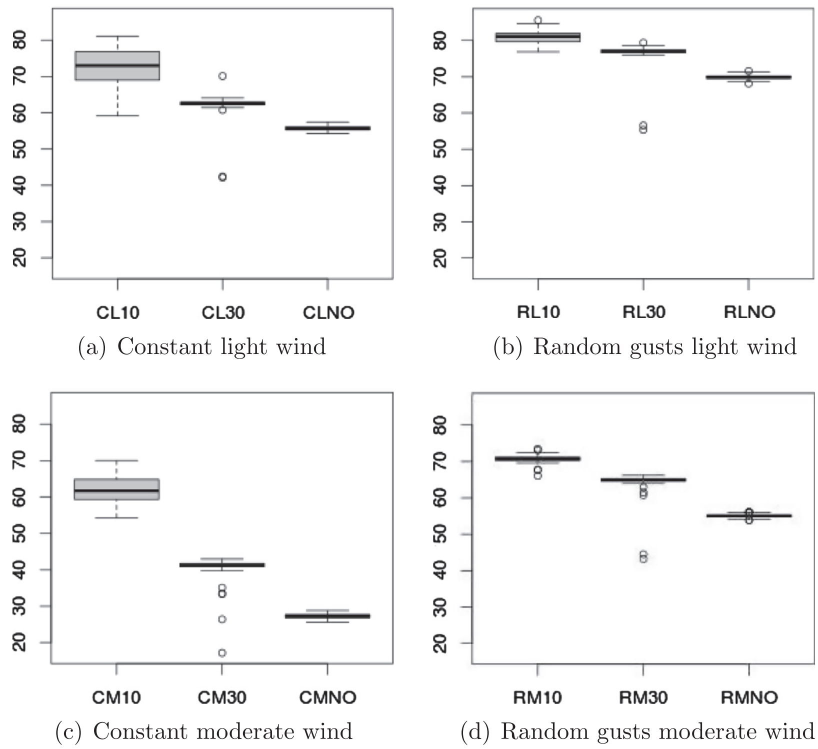

Fig. 5. Amount (%) of chemicals sprayed inside the boundary (results of 70 runs for each parameter set). The parameters can be seen in Table 1.

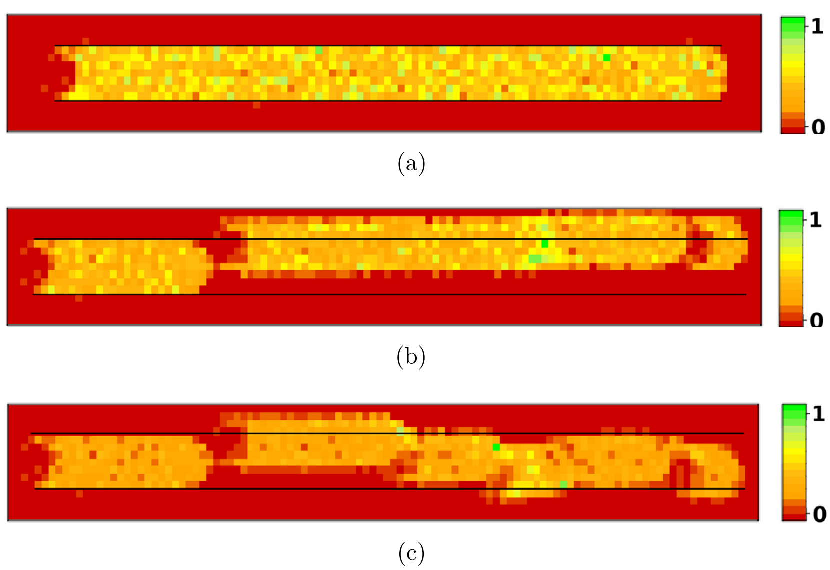

Fig. 6. A heat map to represent the chemicals sprayed on the crop at the end of the simulation. The red color represents no pesticide and green represents the most concentrated places. The thin black lines show the crop field that needs to have chemicals sprayed. (a) Evaluation without wind. This shows almost no chemicals outside the lane. (b) Evaluation with wind changes every 15 s and no adaptation in the UAV route – we can see that the wind makes the chemicals fall outside the boundary lane. (c) Evaluation with wind changes every 15 s and when the algorithm is used to adapt the UAV route – we can see that the algorithm adjusts the UAV by attempting to keep the chemicals within the boundary lane. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on more messages (every 10 s). RL10 is slightly better than CL10 because it has random gusts of wind, which results in having no wind in some parts of the execution. Consequently, the chemical is not affected by the wind the whole time and sometimes goes directly toward the ground. The use of messages every 30 s shows an improvement with regard to the simulation without communication and hence without using the proposed algorithm. In these simulations, the use of messages every 10 s allowed us to improve the chemical dispersion in ≈14% compared with the sets with messages every 30 s and in ≈27% compared with the sets with no messages at all.

We carried out a statistical analysis of the sets to determine if they can be considered to be distinct, and showed the efficiency of the algorithm. First we verified the normal adequacy of the distributions using the Shapiro–Wilk normality test. Most (8 of 12) of the p-values are lower than 0.05, i.e., the hypothesis of normal adequacy is rejected with 95% of confidence. As most of the distributions are not accepted as normal, we carried out a

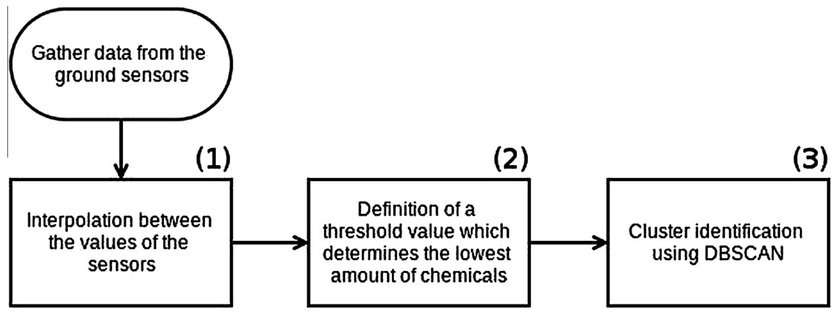

Fig. 7. Steps for mapping the chemical concentration.

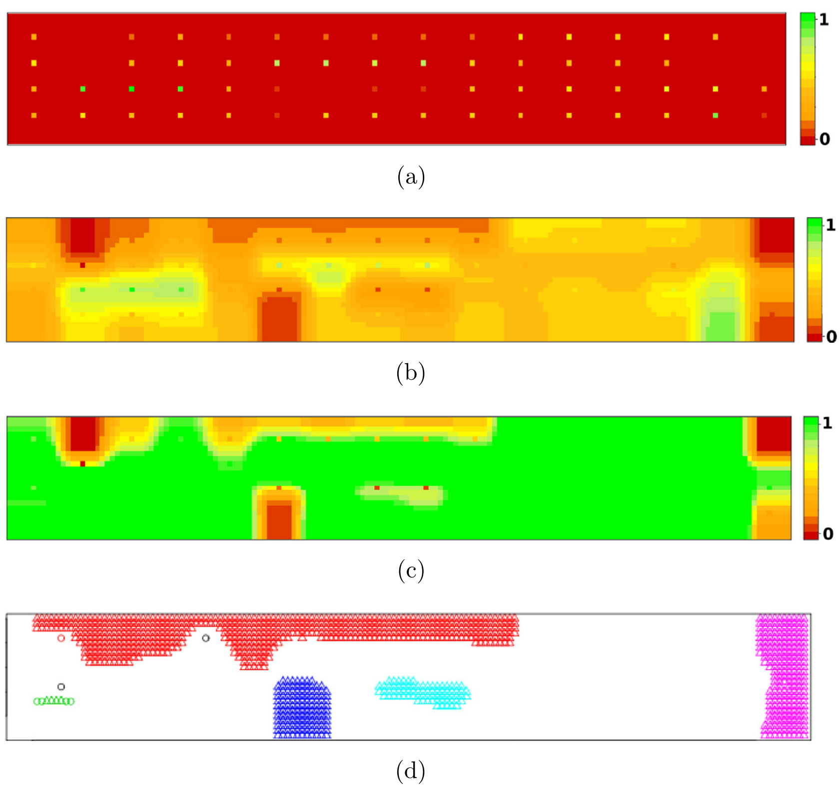

Fig. 8. (a) A crop field represented as a 2D matrix (heat map). A shift from red to green represents less to more perceived chemicals. Most of the area is in red because the sensors are scattered. As expected, the diagram shows a crop field with a non-uniform chemical spraying operation, caused by the highly random wind used in the simulation. (b) Map after the application of the interpolation technique (instance-weighted nearest-neighbor algorithm). (c) Map after the application of the threshold value, which determines the lowest amount of chemicals. (d) Cluster identification using the DBSCAN algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

non-parametric test (Pairwise Wilcox Test) which showed p-values lower than 0.05 in all cases. This means that the algorithm is effective in adjusting the route of the UAV to improve the chemical dispersion. Fig. 6 shows the representation of the chemicals sprayed in the crop field in some of the evaluations. In Fig. 6c we can see how the algorithm adjusts the UAV route and attempts to keep the chemicals within the boundary lane.

4.2. Mapping the chemical concentration

As described earlier, the information retrieved by means of the WSN, provides the UAV with knowledge of the position and the amount of chemicals in every sensor of the crop field. However, after the application of the chemical by the UAV, some areas of the crop might not have a sufficient amount of chemicals; this might occur because the UAV is going too fast and even though the rules allow the UAV to adjust to highly random shifts of wind direction as quickly as possible, it might not be as fast as necessary. As a result, what happens is that there might be some clusters without the correct amount of chemicals. Hence, if we are able to build a chemical concentration map[6] using the data provided by the WSN, we might use this map to show clusters where there is an insufficient application of chemicals.

At the end of the UAV spraying operation, we can build a complete map of the chemical concentration, as we have all the information about the position of the sensors and the amount of chemicals perceived in the UAV memory. The crop field with chemical concentration can be represented as a 2D matrix (Fig. 8a). We represent this map as a heat map, i.e., the amounts of chemicals are represented between the colors red and green, green being the greatest amount.

[6] Source-code and data files used to the mapping scheme are available in http://goo.gl/b0ClX.

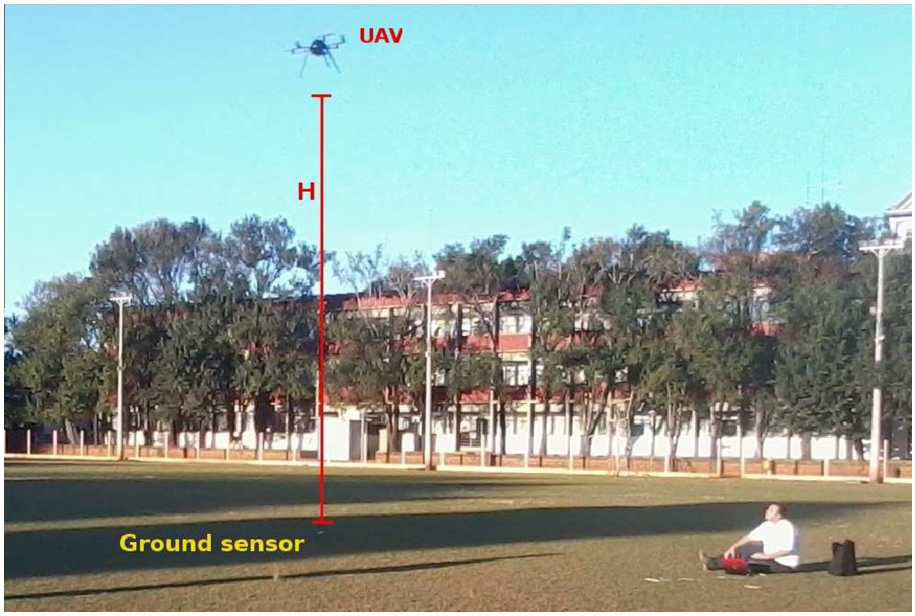

Fig. 9. Example of the real environment used to collect the measurements. We have evaluated *H* with 5, 10 and 20 m.

Table 1
Parameter set employed in the evaluations (with different weather conditions and system characteristics).

Eval.	Wind type	Messages every	Using proposed algorithm
CL10	Constant light wind	10 s	Yes
CL30	Constant light wind	30 s	Yes
CLNO	Constant light wind	–	No
RL10	Random gusts light wind	10 s	Yes
RL30	Random gusts light wind	30 s	Yes
RLNO	Random gusts light wind	–	No
CM10	Constant moderate wind	10 s	Yes
CM30	Constant moderate wind	30 s	Yes
CMNO	Constant moderate wind	–	No
RM10	Random gusts moderate wind	10 s	Yes
RM30	Random gusts moderate wind	30 s	Yes
RMNO	Random gusts moderate wind	–	No

In this simulation, the size of the terrain was set as 1500 m by 150 m. The number of sensors inside the crop field was 64 (4 lines with 16 sensors each). As we were concerned with investigating mapping schemes, we ran this simulation without our proposed adjustment route algorithm and in highly random wind conditions.

We can see in Fig. 8a the representation of the crop field after the application of the chemicals. The red color represents a zero amount, i.e., there is no sensor in that region or the sensor only measured a very small amount of chemicals. In addition, Fig. 8a shows (as expected) a crop field with a non-uniform chemical spraying operation, due to highly random wind.

We ran three stages for cluster identification after obtaining the raw information from the WSN (as shown in Fig. 7). As there are not sensors for every small part of the crop field, it is necessary to make an interpolation between the values of the sensors. Hence, in the first step we use the Instance-Weighted Nearest-Neighbor Algorithm [23] (Step 1 in Fig. 7). This technique is applied in every position of the crop field where there is no sensing information (red area). For each red cell, we calculate the Euclidian distance between its position and the positions of the sensors. Then, the value of each cell will result from a radial function. The closer the chemicals are to the sensor, the higher is their influence on the sensor value. The results of the Instance-Weighted Nearest-Neighbor Algorithm, when applied to the crop field shown in Fig. 8a, can be seen in Fig. 8b.

In the following stage (Step 2 in Fig. 7), we apply a threshold value which determines the lowest amount of chemicals. If the value is below the threshold, it means there were not enough chemicals in the application process. The resulting map after the threshold is adopted can be seen in Fig. 8c.

The last stage (Step 3 in Fig. 7) in the mapping scheme and cluster identification uses a DBSCAN algorithm [15]. The DBSCAN is used to find clusters with an amount of chemicals below the threshold. Using the DBSCAN algorithm, we have to specify a parameter which represents the shortest distance possible between one cell and another to belong to that cluster. Since it aims to provide a completely accurate mapping scheme, this parameter should be measured from real applications. The result of the DBSCAN that is applied in the crop field can be seen in Fig. 8d. We can see five large clusters and three very small ones. We can use the information about clusters to plan a new chemical spraying operation, which is restricted to the delimited areas. Different operations might be taken depending on the size of the cluster (e.g., operations with the UAV or even other types of small autonomous vehicles).

4.3. A step toward a real-world implementation

In the current phase, most of this work has been carried out in simulation environments. With the aim of carrying out evaluations with real hardware, we have measured the communication time between the UAV and a ground sensor, as shown in Fig. 9. We have employed the XBee-PRO Series 2[7] to collect these measurements. Fig. 10 depicts the results obtained from these measurements. The measured communication time consists of the time needed for the UAV to send a request message and receive a response from the ground sensor.

The particular UAV heights (5, 10 and 20 m) were chosen because there is a relationship between the spray angle/coverage and the drone height; the higher the flight, the greater the area covered by the spray. As a result, increasing the distance from

[7] Manufactured by DIGI, http://www.digi.com/products/wireless-wired-embedded-solutions.

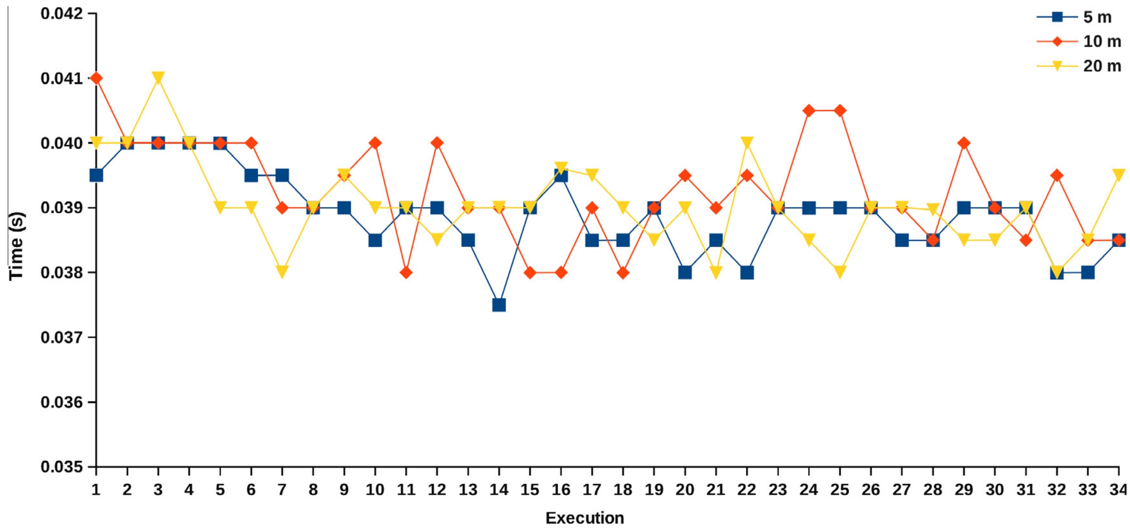

Fig. 10. Time of communication between a sensor ground and the UAV, using XBee-PRO Series 2.

the area where the pulverization is carried out, increases the dispersion of the pesticide. It should be emphasized that environmental conditions also affect the behavior (fall) of the chemicals.

We can notice that the average round trip time for 5, 10 and 20 m is ≈0.04 s. Hence, we carried out a statistical evaluation of the times to check whether there was any significant difference between the 5 m, 10 m and 20 m sets.

Using the Shapiro–Wilk normality test we can observe that there is no evidence that the sets of 5 m and 20 m are normally distributed, with 95% of confidence and the set of 10 m cannot be rejected as a normal distribution, with 95% of confidence. The *p*-values from the Shapiro–Wilk normality test, from 5 m, 10 m and 20 m, are 0.031, 0.056 and 0.006, respectively. Hence, as two of the sets are considered not to be normal, we employ a non-parametric pairwise comparison. The pairwise comparison using the Wilcoxon rank sum test showed that there is no evidence of any difference between the measurements, as all the *p*-values are greater than 0.05. This evaluation has shown that there is no significant difference between the times measured from 5 m, 10 m and 20 m.

5. Conclusions

In this paper we have described an architecture based on unmanned aerial vehicles that can be used to implement a control loop for agricultural applications, where UAVs are responsible for spraying chemicals on crops. The process of applying the chemicals is controlled by means of the feedback from the wireless sensors network that is deployed at ground level on the crop field. Furthermore, we have evaluated an algorithm to adjust the UAV route to changes in the wind (intensity and direction) and the impact related to the number of messages exchanged between the UAV and the WSN. Using the current terrain configuration, we found that the use of messages every 10 s does improve the spraying of the chemical in ≈14% compared to the sets with messages every 30 s and in ≈27% compared to the sets with no messages at all. Moreover, we have also shown how to build a chemical concentration map using the data provided by the WSN. The purpose of this was to show clusters with insufficient application of chemicals which might be used to perform new UAV applications in designated areas. We described how to build these maps using Instance-Based Algorithms and Density-Based Algorithms. The measured communication time between the UAV and the WSN, when the XBee-PRO Series 2 was employed, showed no significant difference for height of 5 m, 10 m and 20 m. All the measured communication times are ≈0.04 s. However this appears to be very short, we have still not been able to assess the actual sensing of the chemicals, which needs to be addressed in the next stage of this research.

6. Future work

The next stages of this project will be as follows: (i) developing the system using real hardware, addressing the reality gap in communications between the UAV and the WSN, the behavior of the UAV and the sensor capabilities, (ii) investigating the use of Evolutionary Techniques [4,1] to build (or tune) an autonomous set of rules (i.e., the behavior of the UAV), and (iii) modeling the system through a UAV swarm technique. As a final observation, since it is necessary to improve the simulation environment (which allows quicker and safer evaluations) other future work should seek to improve the actual chemical dispersion, by also using the mass of the particles, the viscosity of the chemicals and allowing a more realistic interaction between these fluids.

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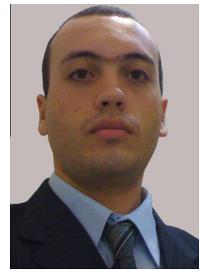

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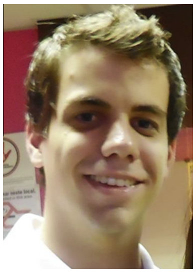

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