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Collaborative UAV-WSN System for Data Acquisition and Processing in Agriculture

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Abstract— **Integration of airborne robotic platforms with networks of intelligent sensor systems on the ground has recently emerged as a robust solution for data collection, analysis and control in various specialised applications. The paper presents a hierarchical structure based on the collaboration between a team of unmanned aerial vehicles and a structure of federated wireless sensor networks for crop monitoring in precision agriculture. Key advantages lay in online data collection and relaying to a central monitoring point while effectively managing network load and latency through optimised UAV trajectories and *in situ* data processing. The experiments were carried out at the Fundulea National Research Institute where different crops and methods are developed. The results demonstrate the fact that the collaborative UAV-WSN approach implemented in the Romanian project MUWI increases the performances both in precision agriculture and ecological agriculture.**

Keywords—crop monitoring; data acquisition; data processing; unmanned aerial vehicles; wireless sensor networks

I. INTRODUCTION

In the last years, new technologies in agriculture and, especially in precision agriculture (PA) have been leveraged for increased productivity and efficient input dosage [1]. For the acquisition and complex processing of data, the integration of unamnned aerial vehicles (UAV) with wireless sensor networks (WSN) under novel frameworks such as the Internet of Things (IoT) contributes to increases of agricultural yields [2].

The WSN has multiple functions at the field level: data acquisition of various parameters e.g. temperature in soil and air, humidity in soil and air, solar radiance, etc., distributed processing of data by establishingconsensus – if it is the case, establishing the relevant data and their retaining, low level data fusion, and data transmission. New sensor node designs offer reduced costs [3]. The hierarchical data processing architecture is based on three level: consensus, fog computing [4], and cloud computing. UAVs also have multiple functionalities like: direct acquisition of data necessary for the monitoring of crop evolution and the anticipated production evaluation. These are done by image processing in visible or multispectral domain. Examples of such applications are the following: states, diseases [5], and damages of agricultural crops. In the losses caused by floods are evaluated by UAV surveillance. The performance of the crop monitoring can be improved by UAV-WSN collaboration [6]. In [7] the authors discuss the information system design supporting agriculture data management. Enabling advanced data processing in the form of sensor fusion and clustering mechanisms for improved network topologies in generic applications has been discussed [6]. Currently effective data gathering mechanisms [8] and higher level IoT architectures [9] are key topics of interest.

We approach the current challenges several directions: a) Precise localization of the ground sensors with the aid of a preliminary flight; b) Sensor states periodically inspected by UAV; c) Establishing of the WSNs as sensor clusters able to cover both sensorial and from communication point of view the monitored area; d) Establishing the cluster heads, named base stations (BS), of the WSNs able to communicate data to UAVs; e) Transmitting commands to change the strategy and parameters of the sensor networks, and f) The aggregation of information collected by the UAV with the information collected by WSN for the purpose of measuring and interpreting the parameters with increased accuracy.

For the main activity, the data collection from BS, UAV must have a predefined trajectory, properly designed account for the following limitations:

- Way-point passing: a UAV has to go above the BS to extract the relevant data from that area (covered by the corresponding WSN sub-network);
- Obstacle avoidance: UAVs avoid obstructions or prohibited areas along the flight plan;
- Guaranteed communication: to ensure that the data has been fully collected, enough time has to be spent in the neighborhood of the BS;
- Efficiency: reduce at a minimum the energy consumption for that trajectory (consider the length of the trajectory and its complexity).

The rest of the paper is structured as follows. Section II describes in detail key aspects that have been addressed for the proper design of such systems. Section III presents experimental result after implementing the system on an experimental farm. Section IV highlights the conclusions as well as future work.

II. SYSTEM DESIGN

A. *Requirements for the Collaborative UAV-WSN*

For the design of reliable and robust large scale monitoring system the requirements have to be first validated. The main challenges for a such collaborative system were considered to be: sensing coverage in accordance to mission objectives, communication coverage by the hybrid UAV–WSN system using various types of radio links, from low-power low-data rate to high throughput long distance for streaming, energy efficiency, and also computing efficiency. The decentralized architecture for crop field monitoring describes in this paper is designed to overcome the challenges further mentioned while accounting for the data generation patterns at the field level. While the proposed data fusion mechanisms and processing of centralized in-field data at gateway level manage to reduce data volume and ensure the flow of information up to the level of events, an additional intermediate level is appended on the data stream, in order to reach the server. The system diagram is presented in detail in Fig. 1. The system was developed in a research project Integrated UAV-WSN-IOT System for Precision Agriculture - MUWI of the University POLITEHNICA of Bucharest, in collaboration with an industrial partner, the company AFT R&D from Romania. The system is composed of four main layers: Sensor layer, Fog computing layer, Internet/ Cloud computing layer, and Data management and Interpretation layer. This is a multi-WSNs, multi-UAVs with higher level integration in Internet-based systems for decision support. The data from WSNs are collected by a team of collaborative UAVs and then transmitted at a ground control station (GCS) and from here, via internet, to the Data interpretation module. Analytics functionality ranges from basic statistical indicators to trend and event detectors and up to basic statistical learning models that have the ability to anticipate evolutions in the monitored ground phenomena.

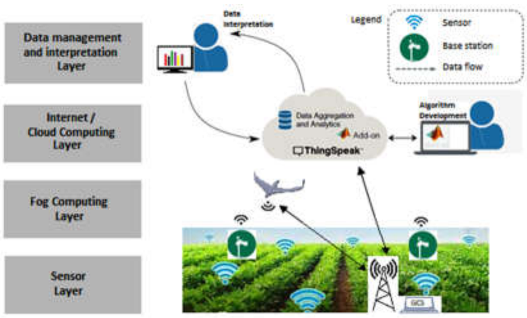

Figure 1. MUWI concept

Other types of similar systems were surveyed and can include the use of swarms of multi-copter type UAVs which offer better positioning accuracy for data collection while trading off energy efficiency and autonomy. Ground sensor network implementation can also a be a differentiating factor with two main approaches: random deployment of sensor nodes in the interest area according to a minimum expected sensing coverage density or deterministic, grid-like placement. Intermediat data processing steps from the field level to the decision level are commonly accepted as an important mechanism to balance network loads and improve communication latency.

B. *UAV Trajectory Design*

Under certain reasonable assumptions (known environment, known limitations), the UAV tasks reduce to computing a trajectory which respects constraints and minimizes a cost (length, total energy expenditure, etc.).

The particularity lies in the fact that many of the UAV-specific constraints are non-convex, e.g., the variable of interest z (depending of time t) has to stay outside some bound (e.g., outside of an interdicted region and / or maintain a minimal velocity). If z(t) is the UAV position, the velocity restrictions are usually written as follows:

$$\underline{v} \leq ||\dot{z}(t)|| \leq \overline{v} \quad (1)$$

Both bounds (lower - $\underline{v}$ - and upper - $\overline{v}$) may depend on a variety of factors. Hard constraints are imposed by the UAV physics: upper bound given by the engine characteristics and lower bound by the requirement to avoid stall. Note that this work neglects the influence of wind: velocity is usually measured against the ground (e.g., through a GPS) but in fact the UAV "feels" the addition of its own and of the wind velocities. This may lead to an expected stall or, at least, improper behavior. Usual techniques are to provide more conservative bounds in (1) and to restrict the flight to normal weather conditions.

Way-point restrictions [10] have, in the more realistic case, a temporal component as well: it is necessary to remain in a specific neighborhood for a defined time interval Δt_i. To describe such a constraint we require thus a tuple $(\omega_i, \Delta t_i, r_i, R_i)$ where ω_i is the corresponding BS_i position (the center of the circle in Fig. 2), r_i and R_i are, respectively, the minimum and the maximunm radius of the permitted communication area. Because there are perturbations due to trajectory control errors or other causes, the real trajectory is included in a flight lane (Fig. 2). The trajectory $z(t)$ has to stay near the way-point for a least amount of time determined by the quantity of data which has to be transferred):

$$r_i \leq ||\omega_i - z(t)|| \leq R_i, t \in [t_i, t_i + \Delta t_i] \quad (2)$$

Condition (2) is often impractical to check due to the continuous nature of $z(t)$ and because of the varying time interval $[t_i, t_i + \Delta t_i]$. The usual approach is to sample the constraint and to estimate the path length by assuming the bounds (1) on the velocity. To this end, we consider:

$$||z(\overline{t}_i) - \omega_i|| = r_i, \quad (3)$$

with $\bar{t}_i$ given such that $\bar{t}_i \in [t_i, t_i + \Delta t_i])$ holds (it is important that a way-point is reached, not when).

Note that the shortest distance for a trajectory checking (4) is the straight line shown in Fig. 2, whose length is $2\sqrt{R_i^2 - r_i^2}$.

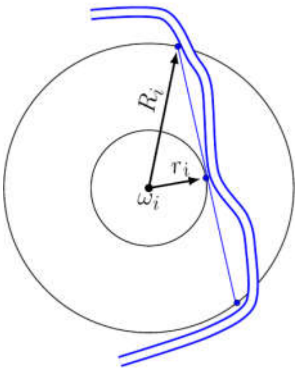

Figure 2. Illustration of inner and outer communication constraints with sufficient condition and a corridor for the UAV trajectory envelope.

In other words, a sufficient condition for guaranteeing that the minimal time Δt_i has passed is to ensure that

$$\Delta t_i \geq \frac{2\sqrt{R_i^2 - r_i^2}}{\bar{v}} \tag{4}$$

Condition (4) provides a lower bound for the time the UAV stays between the inner and outer circles (i.e., how much time it spends inside way-point's ω_i communication range). Then, inserting (3) in a trajectory design procedure implicitly guarantees sufficient communication time. This approach may be insufficient for a couple of reasons. First, the desired communication time may not be known at the trajectory generation time and thus could not be compared with Δt_i. Second, the communication time is known to be larger than Δt_i and a "tangential" pass (like the one enforced by (3)) does not suffice. The method (detailed below) is to enter a *loitering mode* to increase arbitrarily the data-gathering time [11]. Making the reasonable assumption that the loitering r_i^l radius respects $r_i < r_i^l < R_i$ means that the UAV can orbit the way-point ω_i for an indefinite period of time. From the viewpoint of trajectory generation, the only relevant question remains the places at which the UAV inserts/disloges onto/from the loitering circle. Both of these points are decided by the relative position of the current way-point with respect to the previous and next way-points in the sequence (such as to reduce unnecessary inflexions in the trajectory). The switch between normal and loitering modes will be done at pre-determined points: the trajectory enters loitering mode at a point ω_i^- and dislodges from it at a point ω_i^+ (which lie on the loitering circle and are from/towards the direction of the previous/next way-point). Thus, when the UAV decides to finish the communication, it will continue to orbit the loitering circle until it reaches the disloging point tω_i^+. Here it will switch back to the normal trajectory mode.

The inner (dotted line), outer (solid line) communication circles and loitering circle (dashed line) are illustrated in Fig. 3. We show a trajectory inserting to the loitering circle, tracking an arc of it and, lastly disloging from the circle, to re-enter its normal mode. The UAV could have orbited the loitering circle multiple time and disloged from it at ω_i^+ when desired. The trajectory describes a corridor (we account for the inherent tracking error appearing under realistic conditions).

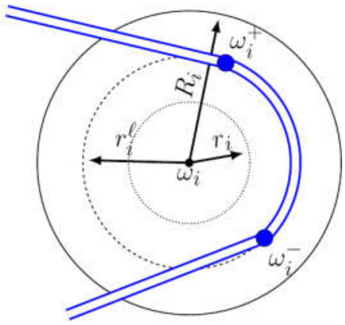

Figure 3. Illustration of trajectory validating.

A case which is not often found in practice is the one where the loitering radius is larger than the maximum communication radius. This means that the UAV cannot communicate with the ground sensor. The idea here is choose a loitering center which is distinct from the sensor's position in order to ensure as much overlap as possible. An illustration of the notion (with the same notation conventions as before) is shown in Fig. 4.

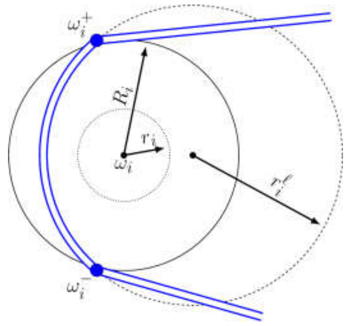

Figure 4. Illustration of trajectory in loitering mode (the case where the loitering radius is larger the communication radius).

In such a case, the variable to be decided is the loitering circle (now distinct from the sensor's position). Note as well that the insertion and extraction points $\omega_i^- \, and \, \omega_i^+$ should now be chosen on the arc of the loitering circle which lies inbetween the communication and exclusion radii.

C. Relevant Data Extraction

In-field data processing is ensured both at local level, independent data filtering and decentralized at network level, through data exchange between neighbour sensory nodes. The proposed data processing mechanisms, tailored for in-field level, are designed in order to ensure a substantial reduction of the measured data volume. The main processing steps are illustrated in the algorithm flowchart provided in Fig. 5. The first step for in-field data processing is performed at local level, independent, by each sensory node. A statistical analysis of the measurement consistency is performed by checking its fitting between the limits imposed by the common three sigma rule. This is found in Fig. 5 as Outlier detection step (A). Further, for a set of consistent value, statistically evaluated using the three-sigma rule, the mean value is computed.

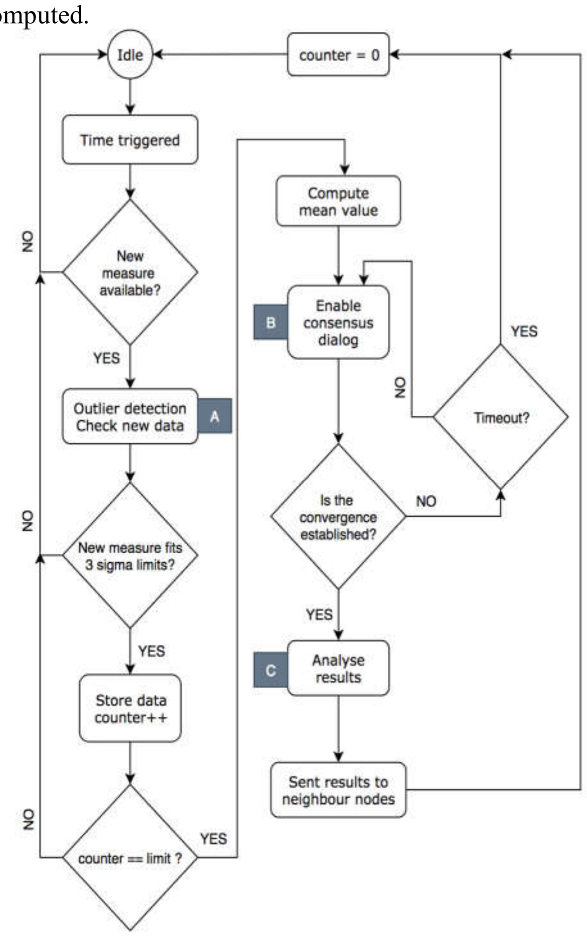

Figure 5. Flow diagram of the data processing steps.

This average value is the relevant value for a certain period of time and is further used to determine a consensus value for a set of neighbouring nodes. The convergence value is achieved by processing the relevant data from each node inside the network, through data exchange and the computation of a weighted average. This step is found as Enable consensus dialog (B). Once the convergence is reached, each node performs a routine for results analysis basically seeking to discover and mark nodes with divergent values. This information remains available alongside the consensus value so that it can be interrogated by the higher level of data processing if needed. This is found in Fig. 5 as Analyse results step (C).

The proposed method for data aggregation is based on using the min and max values extraction, computed as the global extremes for a period of time (e.g. a day). It is obvious that this method is suitable only for measurements that follow a regular shape during time, with smooth variations during a day. A measurement for which this method is suitable is the soil temperature. Instead, change detection is a common method applicable for irregular shaped data sets. This method follows extraction of local extreme points where trend changes occur.

Given a set of data point $(x_i,\ y_i),\ i = 1, \dots, n$, trend t_i is computed for each sequence measurements such that for a measure m, (5), (6), and (7) to be true. If $t_i \neq t_{i+1}$ then it means that trend change occurred, and the data point $(x_i,\ y_i)$ is added to the relevant data set.

$$x_{i+1}^m - x_i^m > \delta^m \Rightarrow\ t_i^m = 1 \qquad (5)$$

$$x_{i+1}^m - x_i^m < -\delta^m \Rightarrow\ t_i^m = -1 \qquad (6)$$

$$x_{i+1}^m - x_i^m \in [-\delta^m, \delta^m] \Rightarrow\ t_i^m = 0 \qquad (7)$$

In-field data processing is ensured both at local level, independent data filtering and decentralized at network level, through data exchange between neighbour sensory nodes. The proposed data processing mechanisms, tailored for in-field level, are designed in order to ensure a substantial reduction of the measured data volume.

Data collection is done periodically, following a succession of specific routines. As mentioned before, the first step for in-field data processing is performed at local level, independent, by each sensor node.

III. Experimental Results

The system was implemented and further extende within the scope of national grant projects with considerable industry participation: Integrated Multi-Agent Aerial Robotic System for Exploring Terrestrial Regions of Interest - MAARS and Integrated UAV-WSN-IOT System for Precision Agriculture - MUWI. The high level configuration of the integrated system is illustrated in Fig. 6. The UAV is of the fixed wing type which enables coverage of large geographic areas with low energy consumption. The base station collects the primary data processed from the field sensors and periodically transmits it to a UAV according to its synchronization with the planned trajectory. Further, the data is processed in the cloud after the UAV uploads the collected data over the Internet.

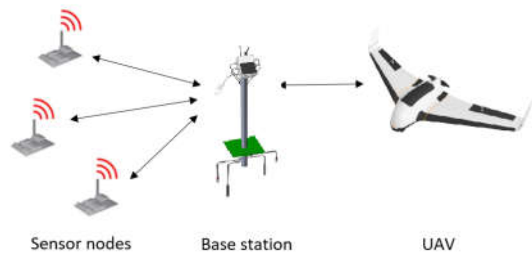

Figure 6. System implementation – General configuration.

Consensus for Solar Radiation

To illustrate the application of the system we present a sample case study for the collection and assessment of solar radiation data. The proposed weighted average consensus was performed for a set of 10 sensing nodes. An in-network data exchange is seeking for the consensus value starting from the average values calculated by each node in part for a set of data collected for 30 minutes. Simulation results are based on TelosB/Tmote Sky platforms as sensing nodes, compatible with Contiki OS. The convergence mechanism is based on RIME communication messages exchanged between neighbor nodes in a random manner.

Fig. 7 illustrates a snapshot of the consensus convergence for the proposed simulation using Contiki COOJA simulation environment. One can observe the value of convergence around 420 W/m^2 and the strong suppression of the two deviated values. Convergence time can be controlled while imposing larger error values or increasing the communication sampling time.

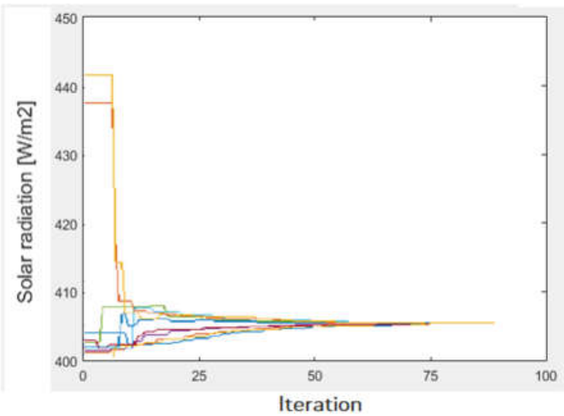

Figure 7. Consensus iteration for solar radiation.

In Table I are presented different time intervals with relevant local points (RP black) for local change trends and relevant global points (RGP) for global change trends (one day interval). The investigated parameters are relevant for multiple crop types. The sample interval is of 30 minutes. Fig. 8 presents a GIS-type visualisation of the deployment for the ground sensor nodes in a agricultural field. The reference node is NC_01 which serves as the local cluster head for all the nodes collecting data in the reference deployment – yellow area.

UAV path planning revolves around optimising the data collection from the cluster head with the constraint of limited mobility and hovering ability of fixed-wing type airborne platforms. To this extent, before the UAV is scheduled to visit the area, all local measurement have to be collected from the WSN at the cluster head, filtered and aggregated while only uploading for example the consensus values, confidence intervals and outcomes of event detection and embedded alerting mechanisms.

TABLE I. DATA PACKAGES SNAPSHOT

T_I HH:MM	**Solar radiation** [w/m^2]	**Tempe-rature** [°C]	**Soil tempe-rature** [°C]	**Relative Humidity** [%]
		...		
11:30	**389 (RP)**	**21.9 (RP)**	20.2	81.2
12:00	227	21.8	20.2	**80.9 (RP)**
12:30	119	21.6	20.3	84.2
13:00	50	21.1	20.4	88.3
13:30	**42 (RP)**	**20.8 (RP)**	20.4	92.9
14:00	63	20.9	20.4	95.1
14:30	167	21.2	20.4	**94.5 (RP)**
15:00	**353 (RP)**	21.7	20.5	91.3
15:30	269	23.4	20.5	85.7
		...		
06:30	155	18.6	20.1	97.0
07:00	232	19.5	19.9	96.5
07:30	233	20.0	**19.8 (RPG)**	95.0
08:00	278	20.5	19.8	92.4
08:30	426	22.1	19.7	88.3
		...		

Figure 8. Real placement of sensor nodes in zone 1.

IV. CONCLUSION

The paper illustrated a case study for collaborative UAV-WSN operation in precision architecture. The main advantages in efficient data collection for the ground nodes and trajectory planning for aerial robotic systems have been discussed. The potential applications in modern agriculture can help offer farmers better insights into the evolution of their crops with direct impact for avoiding diseases and greatly improving economic efficiency, through targeted measures and reduced input usage. Extensive field evaluation is planned for validation of the impact of such a system on crop management.

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