Pasture-based Livestock Identification by Coordenated UAVs

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Abstract. *The increase and improvement of meat production over the last decade is certainly a result of the growing adoption of Information Technology in livestock farming. Precision livestock farming represents a prominent strategy to deliver notable quantitative and qualitative headways and enhance animal welfare and resource management. When managing free-ranging cattle on pasture, there is the problem of identifying, counting and monitoring cattle effectively, despite the extent of the pasture and the dispersal of the animals. Using swarms of Unmanned Aerial Vehicles (UAVs) as cattle data collectors (through readings of RFID ear tags), this work proposes an identification and counting approach to enhance UAV collaboration and routing of the collected data for improved area coverage. The approach integrates coverage algorithms to inventory cattle into a farm management system using some UAVs as the last-mile communication agent. A simulated environment considering pastures of small and medium-sized farms with varying concentrations of cattle supports simulations with an accuracy of 89% for a 16-minute tracking mission, reaching 100% effectiveness for cattle concentration rate within the average density of Brazilian farms.*

1. Introduction

Worldwide, 44% of the world's habitable land is utilized for agricultural and livestock production [Ritchie and Roser 2024]. Brazil has a significant role in this sector, being the predominant beef exporter with approximately 25% of global exports and the second largest beef producer [USDA 2024]. As demand for meat consumption increases, there is a growing need to enhance livestock management in this multi-billion dollar market [Ederer et al. 2023, Aslan et al. 2022]. This involves improving breeding, nutrition, and overall animal health to increase productivity. Livestock management has evolved from small-scale ranching with traditional cowboys to large-scale, intensive, optimized grazing supported by digital technologies and wireless communications.

One emerging strategy in the livestock industry is Precision Livestock Farming (PLF). PLF integrates digital information and communication technologies with affordable sensors for real-time monitoring and tracking of animals [Berckmans 2017]. This animal-centered approach enables rapid identification and management of changes in the health or condition of the smallest production unit, as well as the environmental impact generated by them [Berckmans 2006]. Consequently, it enables timely and accurate detection and handling of issues, even on extensive farms with numerous cattle. For instance, Anna Creek in South Australia, which is among the largest cattle farms, manages 17,000 beef cattle in 2.4 milion hectares of grassland, necessitating the use of PLF. [1] Speed of decision making and execution is also a key driver of farm productivity on such large properties.

PLF has been widely adopted in intensive farming systems, but remains a rarity in pasture-based livestock production. These farms are typically large and have complex livestock management due to the variability and density of the feed base (pasture quality) and the distances covered by the animals [Aquilani et al. 2022]. The implementation of PLF technologies on these farms may prove to be advantageous - or even essential - in promoting animal health and well-being, as well as in preserving overall pasture conservation and facilitating decision-making processes by decreasing expenses.

Real-time animal identification and tracking is a feasible solution for enhancing livestock farm management and reducing resource and cost overheads. Various approaches have been developed for vast open areas, such as pastures, using GPS tracking [Bailey et al. 2018, Koch et al. 2018, Handcock et al. 2009, McIntosh et al. 2022], accelerometers [Werner et al. 2019, Poulopoulou et al. 2019, Sprinkle et al. 2021], or Unmanned Aerial Vehicles (UAVs) [Yu et al. 2013, Li and Xing 2019a, Li and Xing 2019b, Xu et al. 2020, Li et al. 2020]. These approaches have been found effective in monitoring animal locations and behaviors, as well as habitat use and forage intake.

UAVs enable the collection of data about the animals, improving the precision and efficiency of ranching. Additionally, solutions using UAVs for identification and tracking are both scalable and provide automatic tracking at a relatively low operational cost [Li and Xing 2019a]. To identify, track and collect data such as the animal's weight, image capture and manipulation techniques associated with UAVs [Xu et al. 2020, Soares et al. 2021, Xiao et al. 2022] are used. Camera-fitted UAVs execute only the image capturing process owing to processing constraints, whereas information manipulation is undertaken later at a base station to obtain the desired data.

Addressing real-time solutions for pasture area coverage, this research proposes a cattle identification and counting approach that utilizes a swarm of UAVs that collaborate by mutually exchanging RFID data and information for their flight coordination and joint operation of the mission. The general objective is to maximize area coverage within a limited flight time. To validate the cattle head counting and identification using RFID, a non-optimized approach presented in a previous work [Cavalcanti et al. 2023] was extended by inserting decisions in the UAVs movement to change its route to identify more oxen in the surroundings of the previous one.

The main contribution of this paper can be summarized as follows:

- We propose an identification and counting approach for livestock pasture areas using multiple UAVs and RFID;
- We proposed and implemented an algorithm for planning and adapting UAV paths to follow routes with a high probability of finding cattle, based on the fact that cattle in a herd tend to move in groups with little dispersion, and isolated animals are rare;
- We analyzed the cattle movement behavior to improve the mobility of the mobile

[1] https://www.largescaleagriculture.com/home/news-details/top-10-biggest-farms-worldwide/

sensors to capture a more realistic scenario.

The rest of the paper is organized as follows. The study of contemporary techniques and systems is presented in section 2. Our cattle identification approach utilizes coordinated UAVs, as detailed in Section 3. The experimental design and simulation results are presented in sections 4 and 5, respectively. The conclusions and suggestions for future research are discussed in the final section, 6.

2. Related Work

The use of PLF techniques and technologies has become increasingly important in animal health management. Wearable sensors are being designed specifically for livestock, enabling real-time monitoring of vital signs, such as body temperature, pH levels, behavior patterns and stress detection. Early identification of diseases allows farmers to prevent the untimely death of animals [Neethirajan 2017, Halachmi et al. 2019]. Biosensor technologies focus on non-invasive methods to evaluate animal welfare, such as breath, metabolism, and glucose analysis. By executing the analysis locally, transportation of biological samples is also eliminated [Neethirajan et al. 2017]. Cattle behavior tracking [Bailey et al. 2021, di Virgilio et al. 2018] makes it possible to detect diseases, estimate feed consumption rates, grazing intensity and, consequently, overgrazing.

The use of images captured by UAVs is considered a potential and promising alternative for animal identification and counting. The use of machine learning in conjunction with object detection algorithms such as Mask R-CNN [He et al. 2017]. Xu *et al.* [Xu et al. 2020] considers this approach to have revolutionary potential for livestock management because, compared to other technologies, UAVs can: (i) complete flight trajectories at low and ultra-low altitudes; (ii) obtain high-resolution images at any time; and (iii) quickly acquire images over small areas and inaccessible rugged terrain. Recent studies suggest that the use of multiple UAV systems may be beneficial in expansive agricultural environments, as it has the potential to minimize flight duration, battery usage, and cost [Erdelj et al. 2019, Mammarella et al. 2022, Aslan et al. 2022, Ju et al. 2022].

Using UAVs with external processing of the Mask R-CNN object detection algorithm, Xu *et al.* [Xu et al. 2020] was able to realize livestock detection and counting from the captured images, using as the essence of detection the binary classification with both confidence and masking. The obtained results had a confidence rate ranging from 84% to 95% depending on the context (height of the UAVs, occlusion, illumination, and overlap). However, the solution does not identify whether an animal has already been detected, resulting in false positives due to duplicate counts of some cattle. Improvements to Mask R-CNN were made by Xiao *et al.* [Xiao et al. 2022] by adding animal identification and increasing the average detection accuracy to 98.67% using images captured in a barn.

Barbedo *et al.* [Barbedo et al. 2020] points out the problem of identifying animals when they are in a cluster, where the boundaries of the animal's body become blurred. Using a similar approach of Xu *et al.* [Xu et al. 2020] and Xiao *et al.* [Xiao et al. 2022], Barbedo *et al.*uses the NasNetLarge [Zoph et al. 2018] deep learning cattle detection algorithm to train a CNN model for regions classification according to the presence or absence of animals, which is used in more three steps - color space manipulations, mask combination to separate clustered animals, and feature matching - to identify and count cattle. Tests were made using images captured by UAVs flying over a pasture area during different times of the day and of the year and weather condition. The images were also tallied at three different levels to improve the identification and counting accuracy from 71%, when the animals are in cluster, to around 95%. The Barbedo algorithm is expected to produce that accuracy for pasture areas until four animals per hectare.

Barbedo *et al.* [Barbedo et al. 2020] also discuss the challenge of identifying animals when they are in a cluster, which can cause the boundaries of their bodies to become blurred. Barbedo *et al.* [Barbedo et al. 2020] employed the NasNetLarge deep learning cattle detection algorithm to train a CNN model for region classification based on the presence or absence of animals, following a similar approach to Xu *et al.* [Xu et al. 2020]. The model was used in three steps: color space manipulations, mask combination to separate clustered animals, and feature matching, to identify and count cattle. Tests were conducted using images captured by UAVs flying over a pasture area at various times of the day, year, and weather conditions. The images were tallied at three different levels to improve identification and counting accuracy, increasing it from 71% (when the animals are in a cluster) to approximately 95%. The Barbedo algorithm is expected to produce this level of accuracy for pasture areas with up to four animals per hectare.

Within the context of detection-based identification, Soares *et al.* [Soares et al. 2021] proposed a method for detecting and counting cattle in aerial images taken by UAVs, based on convolutional neural networks (CNNs) and graph-based optimization to remove duplicate animals detected in overlapping images. Tests were conducted using images captured by cameras mounted on UAVs flying at altitudes ranging from 12m to 90m over pasture areas ranging from 50ha to 90ha. This approach proved to be highly effective for both detection and counting, even when using a smaller number of images with little overlap between them. This allows for greater UAV autonomy and larger area coverage, considering pastures areas with animal density varying from 1 to 18 animals per hectare. However, it should be noted that this method does not identify individual animals.

The *Ear tagging* is the oldest and simplest solution for animals identification, requiring contact for identification of visual patterns. Following the same visual patterns, the current *Ear Tagging* is being replaced by *RFID Ear Tagging*, which uses radio frequency communication to send the animal's ID. RFID provides an easy and efficient way to control, track and monitor livestock [Ruiz-Garcia and Lunadei 2011], without the need for human intervention.

Unlike most counting and tracking approaches, Alanezi *et al.* [Alanezi et al. 2022] proposed to use the geographic coordinates of the pasture field to optimize the communication and flight patterns of the UAVs before starting the perimeter scanning. Information such as the size of the pasture and the maximum flight time are also used to determine the number of UAVs needed and the area coverage algorithm. Cattle identification is not performed, but the defined algorithm ensures maximum coverage with the least amount of resources and can be used in both image and RFID identification solutions.

Li *et al.* [Li et al. 2020] proposed a cloud-based grazing management system integrated with a decision-making tool based on WebGIS. The system employs both UAV and satellite remote sensing (RS) images to identify and track individual oxen in the herd, providing real-time positions and historical tracking information. These data are essential for monitoring animal behavior and health, as well as for grassland monitoring and growth estimation to prevent overgrazing and grassland degradation. Systems proposed by Li *et al.*consist of combined sensors that furnish farmers with adequate information on animal behavior, health, and location. But it also has problems with a higher cost for its implementation in the field and maintenance, especially regarding battery life and device replacements.

Table 1. Key features of the current state of the art and the proposed approach.

	Characteristic	Xu	Barbedo	Soares	Li	HICA
Features	**Cattle counting**	Yes	Yes	Yes	Yes	Yes
	Oxen identification	No	Partially	No	Yes	Yes
	No Double counting	No	Yes	Yes	NI	Yes
	Real-time processing	No	No	No	Yes	Yes
	Counting Accuracy	90%-94%	95%	96%	NI	89%-100%
Technology	**Tracker Device**	UAV	UAV	UAV	UAV and GPS	UAV
	Identification based technique	Image	Image	Image	Image and GIS	RFID
	Virtual fence	No	No	No	Yes	Yes
System Integration	**Management System**	No	No	No	WebGis	HMT
	Decision make support	No	No	No	Yes	Yes

* : Improved Mask R-CNN

Characteristics of features (identification, counting, and real-time processing), technology (devices and techniques), and system integration for improved cattle management were analyzed. The four main works discussed in this section, which that detects and count animals in pasture areas, are presented in Table 1 and compared against the herd identification and counting approach (HICA) proposed in this article, which encompasses all of these characteristics. Table 1 shows that all approaches execute oxen detection and counting, but only Li *et al.* [Li et al. 2020] and HICA perform identification. The final one also detects missing cattle since the tracker UAV possess knowledge of the animal IDs that should be present within the grazing location, and Li also does this to some extent. Li and Soares address possible counting errors caused by double counting. Considering the characteristics of the technology, all solutions use drones with attached cameras and image processing for tracking and counting, except for HICA which utilizes drones and RFID. From Table 1, it can be observed that this approach is more similar to Li's in terms of features and integration into a larger management system. They differ in their technology. Li employs images captured by drones and satellites, while HICA uses RFID technology for tracking and identification that is not yet widely explored in real-time capture through mobile devices such as UAVS.

3. Herd Identification from the Air

This work proposes an approach to identify mobile nodes on the ground using UAVs. The overall idea is to provide an efficient and reliable method to scan, identify and collect information from the mobile nodes within a predefined area using UAVs, that also communicate with each other. The UAVs begin the mission with a predefined path that can be modified based on the presence of mobile nodes nearby. They exchange information with other UAVs to obtain data that has already been collected, reducing the time spent tracking the area. Identification is achieved through communication between the UAV and the mobile node, using technologies such as Radio Frequency Identification (RFID), Bluetooth Low Energy (BLE), and Long Range (LoRa).

Given the mobility of cattle and the expansive nature of pasture-based livestock operations, monitoring the herd in pasture areas is effectively achieved through this approach. The use of land vehicles or human intervention may cause undue stress to the herd, resulting in increased frequency and intensity of movement. UAVs flying at a safe altitude should not disturb the cattle. This is particularly advantageous due to the vast scale of Brazilian agricultural properties and pasture areas. Furthermore, the use of ear tags with RFID for identification purposes allows for cost-effective system deployment, faster area coverage, and real-time monitoring. Given this scenario, the proposed approach will be explained using cattle as mobile nodes and communication through RFID.

The identification algorithm analyzes a scenario with five primary components, outlined in Figure 1. These elements comprise a (i)*ground station*, which transmits configuration information to the UAVs, receives and store data collected by the UAVs and functions as the launch site for the UAVs; (ii)*reader UAV (R_i)*, which collect sensor data while flying above; (iii) *tracker UAV (T)* which detect UAVs within a specified area defined by a (iv) *virtual fence*; and (v) *mobile sensors* (RFID tags attached to each animal in the herd).

The UAVs acquire a collection of waypoints from the ground station, which define a virtual fence (points labeled as (VT, w_k) in figure 1), a set of waypoints mapping out their mission route, and a list of UAVs scheduled to take part in the tracking mission. If a UAV is given identical sets of waypoints for the virtual fence and the mission route, it is classified as a tracker UAV. Conversely, if it is given distinct sets, it becomes a reader UAV. The UAVs for reading purposes traverse paths established at the start of the tracking process, but unique from one another for maximum coverage of the virtual fence's designated area. In Figure 1, we can see the routes taken by the reader UAVs, which are represented by points labeled as (R_i, w_j), where *i* is the number of the reader UAV and *j* is the number of the waypoint (*e.g.,* (R1,w4) is the fourth waypoint of the reader UAV 1). During their journey, the reader UAVs transmit RF request signals, and upon receiving response signals from the tags, they store them, updating their list of collected IDs. When UAVs enter the communication range of other UAVs, whether they are readers or trackers, they exchange their lists of collected identification codes. This results in the communication concluding with a single merged list that excludes any duplicate identification codes. The UAV used for tracking also acts as a reader, following a predetermined route over the waypoints that define the perimeter of the virtual fence. It identifies all relevant detections within the designated region.

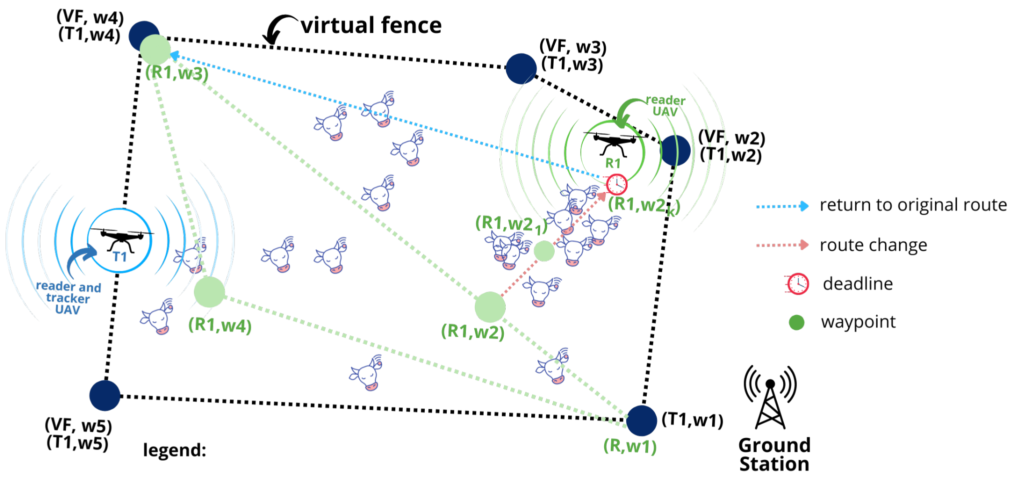

Figure 1. Scenario elements for cattle identification.

3.1. UAV Route Change Algorithm

Each R_i is assigned a unique mission consisting of a route defined by waypoints that covers a specific region of the area, as designated by the ground station. Once initiated, R_i moves towards the next waypoint on its route. During the mission, the UAV sends out RF signals and waits for a response. When a response is received, including the bovine ID, the system stores both the ID and the geographic coordinates of the location where the message was received.

Considering that cattle are widely regarded as social animals that generally live and travel in groups to reduce the risk of predation [Doyle and Moran 2015]. Furthermore, living and moving together tends to have a pacifying effect on cattle, resulting in lower stress levels. The UAVs could focus on identifying the regions where groups are rather than realizing a complete scan of the area. Based on this, if any R_i detects a group of cattle that has not yet been identified, it starts a timer *T*, stores the subsequent waypoint of the original path and calculates a new waypoint to a nearby point where other mobile sensors might be. To do this, R_i calculates the mean value of the geographic coordinates of the group and adds it as the next waypoint, while continuing in the new direction until the timer *T* ends. If during the time *T* other new cattle have been identified, R_i repeats the calculation of the new waypoint. Otherwise, the UAV changes its route to the original waypoint stored before the route was changed.

The presence of cattle near waypoint $(R_1, w2)$, as illustrated in Figure 1, causes a route change of the reader UAV (R_1). Initially, the UAV starts its tracking mission by following a predetermined path consisting of $w1 - w2 - w3 - w4 - w1$ waypoints. When the $w2$ waypoint is reached, a group of cattle is identified, then R_1 starts the procedure to change its route. R_1 starts the timer T and stores the next waypoint on the original route $w3$. The mean geographic coordinates are calculated and a new waypoint $w2_1$ is added as the next stop on the new route. R_1 continuously calculates new coordinate waypoints until it ends T and no more cattle have been identified. At this point $(w2_k)$, R moves to the next waypoint, $w3$, along the original path stored before the route change and follows it until it reaches the end point or detects another group of cattle, causing the route to be changed.

If R_i enters the communication range of any R_j during any part of the mission, they exchange their lists of collected identification codes. With this information, R_j updates its list of ID codes and does not implement the route change if it identifies cattle already identified by R_i or R_j.

3.2. Communication Standards

Communication between UAVs and between UAVs and the ground station can use any radio frequency communication standard. For 98% of Brazilian farms with land areas up to 500 hectares [IBGE 2021], Wi-Fi and LoRa (Long Range) were examined as options for communication between UAVs and Ground Stations, as well as between UAVs. Technical abbreviations will be explained on first use throughout the text. The transmitted data includes localized identifiers, respective locations, and data from attached sensors.

The communication between UAVs and cattle occurs via radio frequency in the ultra high frequency (UHF) standard RFID, operating at a frequency of approximately 915MHz. The tags are defined by UHF ISO/IEC 18000-6 [ISO 2013] or EPC CLASS 1 GEN2 860-960 MHz [EPC 2005] Passive RFID Tag. The tags have a reading range limit of 15 meters, which enables the UAVs to fly at a safe distance above the flight zone of the cattle. The term 'flight zone' refers to the area within 3-5 meters from the animal that can trigger a threat response, causing the animal to move or flee [Doyle and Moran 2015].

4. Experiments Architecture

The proposed approach was implemented and simulated in GrADyS-SIM [Lamenza et al. 2022, Olivieri et al. 2021]. This simulator extends the INET++ [INET 2022] networking library supported by the OMNET++ framework [OMNet++ 2022]. GrADyS-SIM is well-suited for implementing and simulating drone swarm coordination strategies to gather sensor data in the field. It is utilized for observing drone movement, message exchange, and validating the communication implementation between *drones-ox-ground station-cloud* and the quality of the area tracking algorithm.

Based on data from the Brazilian Institute of Geography and Statistics (IBGE), nearly 98% of agricultural properties in Brazil are small or medium-sized, encompassing farms up to 500 hectares [IBGE 2021]. Utilizing this information, we created simulations in GrADyS-SIM featuring pasture areas of 100, 225, and 400 hectares. The pasture areas were modeled as polygons, delineated by joining geographical points as shown in figure 1, in the area delimited by the virtual fence by the waypoints *(VF,w1)-(VF,w2)-(VF,w3)-(VF,w4)-(VF,w5)-(VF,w1)*. The dimensions were determined through empirical analysis of small and medium-sized properties to investigate the effect of herd size and density on the accuracy and efficiency of animal identification and counting.

For these three distinct farms size, a sequence of simulations was performed using 16, 32, 64, 100, and 200 cattle equipped with with RFID tags to assess the performance of the algorithm in identifying low-density animal populations. This was carried out up to the real average density of around 1 head per hectare in Brazil. The evaluations were aimed at ascertaining whether the algorithm was effective or not. Based on the discussion in section 3.1 regarding the movement of cattle in groups, simulations were conducted by dividing the herd, respectively, into 2, 3, 4, 5, and 8 groups of similar size. Each group was led by a designated leader responsible for the trajectory of the group's movement.

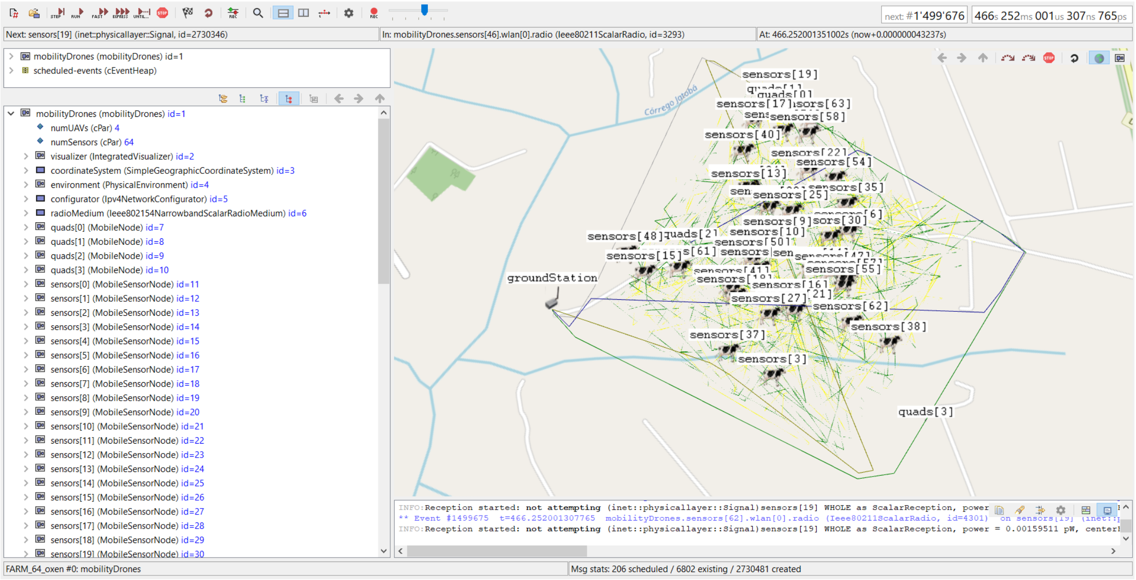

Figure 2. HICA simulation in GrADyS-SIM with 4 quadicopters and 64 oxen.

The simulation scenarios took into account the previously reported property sizes and number of oxen, and involved missions performed by four UAVs. To cover the designated areas, the UAVs were simulated as quadcopters modeled as *MobileNode*. The quadcopters have a DroneMobility mobility model and utilize the HICADroneProtocol protocol. Communication between drones occurs via UDP using Wi-Fi and between mobile sensors via RF. Figure 2 presents the 3D view of a simulation conducted using four quadcopters and sixty-four oxen in a 225-hectare pasture area, using GrADyS-SIM technology. This simulation visualizes communication information, including the packages exchanged between quadcopters, mobile sensors, and ground stations.

The HMT (Herd Management and Tracking) application [Cavalcanti et al. 2023] was used to model the farm before running the simulations. The HMT application is a comprehensive cattle management platform that takes an individualized, animal-centric approach, from simply identifying each animal to tracking veterinary and pasture data. It monitors the information extracted from HICA and communicates with the farm simulation over the Internet through the ContextNet middleware [Endler and e Silva 2018], which preprocesses the information. Its web interface displays system information such as drone and herd lists, tracking information, and allows requests to read data.

The graze tracking was requested through the HMT application [2] to initiate the simulations. Farm details, including the name, oxen, drones, and virtual fence, were inputted and saved. This feature sends pertinent information, such as the number of oxen, virtual fence delimitations, and drones involved, to the ground station. At the conclusion of the simulation, the HMT app receives a comprehensive list of oxen whereabouts and presents it, specifying the quantity and identification of absent oxen, as well as their grazing times, initially and in conclusion. Each grazing tracking's data is stored and utilized for creating reports exhibited on the app dashboard.

[2]HMT App Github Repository. `https://github.com/milliandrade/hmt_sw`

4.1. Experiments in GrADyS-SIM

All components introduced in section 3 were implemented as nodes in GrADyS-SIM. The nodes consist of three parts: mobility, communication protocol behavior, and the communication interface itself. The nodes were implemented as an extension of the GrADyS-SIM modules *MobileNode*, *MobileSensorNode*, and *GroundStation*. The communication protocol behavior was implemented as a new protocol called *HICAProtocol*. It enables the information exchange between UAVs and other system components and also implements the HICA approach.

The mobility behavior of the UAVs and GroundStation follows the *DroneVMobility* and *StationaryMobility* models, respectively. The cattle's mobility involves two types of movement: the leader moves using the *LinearMobility* mobility model, while the others use *AttachedMobility*, which is related to their leader, to follow the leader's movement. All mobility models were provided by GrADyS-SIM and transfer telemetry data to the node's communication protocol. The protocol then defines movement commands based on the gathered information and input from other nodes.

5. Results

Small and medium sized farms were considered in all simulations, created and executed as defined in section 4. Each of the 15 possible scenarios was executed 10 times, and an arithmetic mean of each observed parameter was calculated. Based on these constraints, and with an average quadcopter battery life of 30 minutes, we analyzed the correlation between the following parameters: (a) property size, and (b) cattle concentration ratio (CCR), determined by the average number of cattle per hectare, and (c) cattle identification and counting accuracy. We tested for all possible associations between these parameters and present our results in Figure 3. The figure shows the average cattle identification accuracy of the configurations using 4 UAVs. Data related to configurations in areas of 100 hectares achieved 100% accuracy in all simulations, indicating that 4 drones with a sixteen minute mission should be sufficient to identify all animals in the defined area.

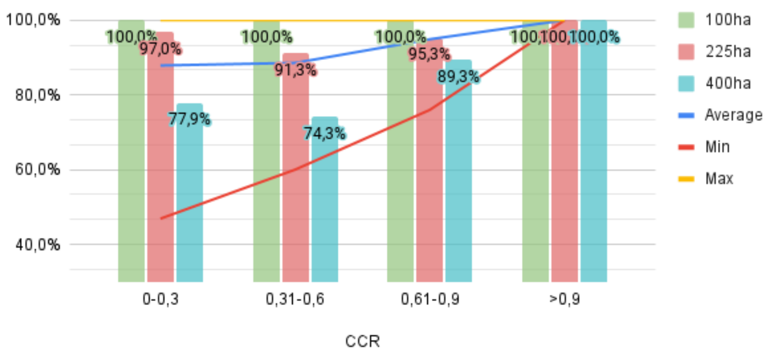

Figure 3. Cattle identification and counting accuracy in pasture areas of varying sizes (100ha, 225ha, and 400ha) when using four UAVs for different cattle concentration rates.

Analyzing the information obtained, the approach has achieved an assertiveness of over 92% in areas with a CCR above 0.6 and a tracking execution time of 27 minutes. With a concentration rate above 0.9 cattle per hectare, which is still below the national average, the algorithm demonstrated a 100% level of assertiveness. Due to the computational limitations of the simulation environment, concentrations of up to 2 were tested, with 100% assertiveness maintained. Compared to the previous approach [Cavalcanti et al. 2023], HICA showed better results at lower CCR, taking into account a more realistic animal movement behavior and improving the average requirement of a drone from 30 to about 50 hectares to maintain an assertiveness above 92%. Unlike the previous studies [Xu et al. 2020], [Soares et al. 2021], and [Xiao et al. 2022], which used UAV-based tracking and image processing for animal identification, the increase in CCR is better for the HICA approach when the cattle clusters do not pose a challenge for RFID identification, considering the maximum physical number of animals in the antenna communication range. The current study also achieved similar counting accuracy rates to the other presented works, with the difference of counting in real time at the same time that the animal is identified.

Another relevant point to highlight is the lack of real-time data acquisition and presentation in the presented studies of image processing. This is due to the fact that the algorithms are not executed locally and do not have timely communication with the external processing node. Additionally, there is a lack of duplication in herd count.

Nonetheless, this study utilizes simulation-based results, which may differ from real-world conditions. With the aim of a practical simulation, the simulator employed as many parameters as possible to represent a genuine environment. Another factor to consider is the movement of the animals, but since measurements are taken rapidly and the animals act as stationary sensors due to their positions remaining relatively unchanged during the tracking period, any discrepancies between the real and simulated cattle movement models are unlikely to significantly impact the results.

6. Conclusion

The increasing use of FPL, particularly in pasture-based systems, necessitates the refinement of rural farm and activity management. The application of IoT and sensing technologies can optimize rural farm management, providing real-time data for decision-making and enabling mobile device-controlled management of specific areas of the property through the use of UAVs.

In this context, this study presented a herd identification and counting approach using coordinated UAVs. This work has yielded better results than comparable methods presented in Section 2 and from the previously non-optimized approach implemented [Cavalcanti et al. 2023]. It presented a 100% accuracy for areas with cattle concentration ratio equals or superior from brazilian farms CCR, 16-minute flight, and 92% effectiveness for cattle concentrations above 0.9 head per hectare in a 27-minute flight mission, with no double counting of animals. This approach is noteworthy because it takes advantage of existing infrastructure on the property, including RFID Ear Tagging in cattle, network infrastructure, and UAVs. In addition to its high success rate, this method is cost-effective and has a shorter implementation time, allowing for more efficient decision-making and response times.

Based on our results and experience implementing the solution, we expect to improve or maintain excellent detection rates with fewer drones or reduced tracking time by improving area scanning and coordination algorithms. To develop this solution in the short and mid-term, we identified improvements with the evaluation of the proportionality of UAVs per area. The UAV coordination algorithm can also be improved by incorporating consensus decision making, subgroup organization, and dispersion for the large area scan, taking into account scans with and without a predefined route.

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