Smart Collars for Sheep: Leveraging Machine Learning for Improved Pasture Management

Gonçalo Soares, Paulo Pedreiras
DETI and IT, Universidade de Aveiro;
Aveiro, Portugal
e-mail: {goncalo.soares01, pbrp}@ua.pt

William Xavier
iFarmTec and Wiseware
Gafanha da Encarnação, Portugal
e-mail: william@wisewaresolutions.com

Pedro Gonçalves
ESTGA and IT, Universidade de Aveiro
Aveiro, Portugal
e-mail: pasg@ua.pt

***Abstract*— Effective control of animal feed and pasture management are increasingly important factors for animal health and farm sustainability. Recent technological advances in animal monitoring devices offer a significant potential for enhancing these practices. This paper presents the development of an innovative animal monitoring system for sheep, designed to capture images of pastures while minimizing redundant data collection. By integrating Machine Learning (ML)-based animal posture detection, the system autonomously triggers image acquisition only during relevant feeding activities. Additionally, the system automatically uploads the captured images for processing, reducing the need for manual intervention. Preliminary results demonstrate the system's feasibility and improved efficiency compared to state-of-the-art approaches.**

***Keywords-component; Ruminant monitoring; grazing behavior; floristic analysis*.**

I. Introduction

The control of animal feed and the management of pastures are essential for maintaining animal health and ensuring the economic sustainability of farms. Recent technological advances have made it possible to utilize animal monitoring devices, which can play a crucial role by collecting and processing data about animals' feeding behavior—data that was previously impossible to gather. These devices enable the collection of data for multiple purposes, including identifying feeding patterns, tracking areas of pasture, categorizing the plants consumed, and estimating the amount of nutrients consumed.

In recent years, there has been an increasing number of studies and technical solutions in the field of animal monitoring. These systems often incorporate various sensors, including video cameras, to support the monitoring process in diverse ways, *e.g.* observing behavior and activity, migration routes and location.

The approaches reported in the literature typically involve collars equipped with cameras configured to take photos at regular intervals during specific periods. Some collars also feature localization devices, such as Global Navigation Satellite System (GNSS) receivers, to identify feeding patterns. Despite providing valuable information, state-of-the-art approaches have inherent limitations that hinder their widespread adoption. For instance, image recordings are either pre-programmed or manually activated. Pre-programming often results in a significant amount of redundant or useless data (e.g., multiple photos of the same pasture, or photos taken when the animal is not eating) (see e.g. [1]). These unnecessary images consume a significant amount of memory and energy, limiting the autonomy of the devices and requiring substantial post-processing effort, often dependent on manual intervention. Manual activation, however, requires systematic human supervision, which is usually unfeasible. Moreover, these devices typically require manual intervention to collect and upload images to processing platforms, making the process cumbersome, inefficient, and costly. Another significant limitation is the use of Commercial Off-The-Shelf (COTS) cameras with low battery capacity, necessitating additional batteries that significantly increase the collar's total weight and size.

This work addresses the aforementioned issues and limitations of state-of-the-art approaches, with the primary objective of developing an animal monitoring device for sheep that captures images of the pastures and location while the animals are feeding. The device integrates Machine Learning (ML)-based animal posture detection functionalities, triggering image acquisition only at relevant moments, such as when animals begin eating after moving to a new location. Furthermore, the system automatically uploads images to a processing platform. These features result in a system that operates autonomously, with extended battery life, and minimizes redundant data, significantly improving cost, efficiency, and usability compared to state-of-the-art approaches.

This paper presents the initial steps toward developing this system, including its architecture and collar implementation. Preliminary results are also included, demonstrating the feasibility of the approach.

The remainder of this paper is organized as follows: Section II briefly reviews the state-of-the-art. Section III presents the system architecture. Section IV includes functional and performance results. Finally, Section V concludes the paper.

II. State of the Art

In recent years, there has been a growing number of studies and solutions in the field of animal monitoring. These studies often incorporate various sensors, including video cameras, to support the monitoring process in diverse ways, such as observing behavior [2], activity [3], feeding habits [1], births [4], habitat choices [5], migration routes [6], and location [7].

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For example, a study presented in [5] monitors the feeding sites and habitats of pregnant migratory females of the Rangifer tarandus species during the summer. Sixteen females were fitted with Vertex Plus [8] collars that integrate a GNSS receiver and a camera. The collars were set to record ten-second video clips every 20 minutes, resulting in a total of 200,000 videos. These videos were then individually analyzed to identify those containing useful information for the study, which were around 25,869 videos. Another study focuses on analyzing the grazing behavior of sheep using collars with Point Of View (POV) cameras [1]. The study had a twofold objective: analyzing the feeding habits of sheep during the spring and determining if the behavior of a subset of sheep fitted with cameras could represent the behavior of the entire flock. The cameras were affixed to the sheep collars, along with a GNSS receiver and a set of batteries that extended the recording time. The cameras recorded video clips at fixed intervals throughout the day, resulting in a recording period of six to eight hours per day per sheep. This study provided valuable information about the animals' diet and revealed a relationship between the activity of the flock and the activity of the sheep with POV cameras.

Despite their value, these approaches face scalability and mass adoption challenges due to the significant amount of irrelevant information collected, resulting in inefficiency and autonomy limitations, and the dependence on human intervention at several stages.

III. SYSTEM ARCHITECTURE

The architecture of the system proposed in this paper is shown in Figure 1. It includes a collar with inertial sensors and a camera that captures images when a suitable software trigger is issued. The collar has a Bluetooth Low Energy (BLE) interface that connects to a data aggregation gateway located in the animal's shelter. When a collar and a gateway are within communication range, the images and accelerometer data stored in the collar's internal memory during the grazing period are uploaded to the gateway. The gateway, in addition to aggregate data from the various collars, contains a Tensor Processing Unit (TPU) [9] that identifies the species photographed through a previously trained learning model. The system also comprises a cloud-based application that centralizes information sent from one or more shelters and/or farms. Among other functionalities and uses, the collected data is used to train, in real-time, the image identification model. The updated model parameters are then sent back to the gateways' TPUs, to improve the performance of the species identification mechanism.

Image capture is based on the animal's behavior. The collar continuously monitors the animal's behavior via inertial sensors (accelerometers, in the case) and classifies them according to a previously defined ethogram [10]. Whenever it detects that the animal is eating in a new place, it triggers an image acquisition, to ensure that representative data is collected, while reducing redundancy. Images are saved in an internal memory of the collar, and they include a time stamp that allows the moment of collection to be identified.

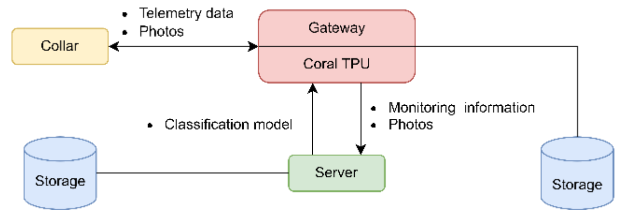

Figure 1. System architecture.

The data transfer between collars and the gateway is done through an opportunistic communication mechanism. To this end, collars periodically emit a BLE beacon [11], which, when detected by the gateway, triggers the information transfer process, which is illustrated in Figure 2. The gateway can connect to up to five collars simultaneously, allowing five data transfers to take place at the same time. As soon as the gateway connects to a collar, it sends the Get Info command, to which the collar responds with information about the device. The information packet sent by the collar to the gateway includes fields such as device ID, timestamp, animal type, battery status, number of files, and number of photos.

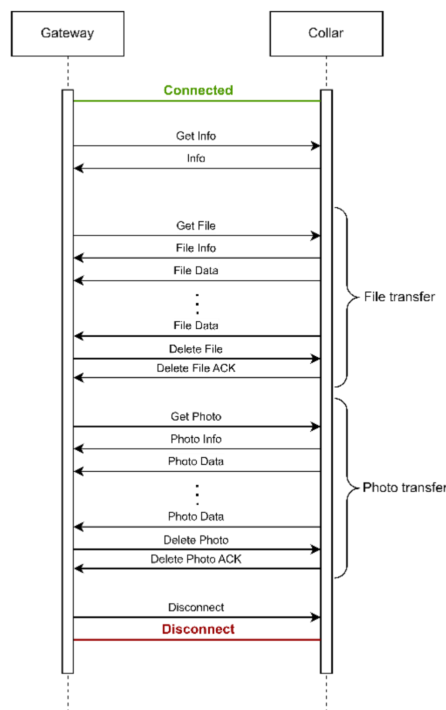

Figure 2. Information transferred between collar and the gateway.

If there is data or photos to transfer, the gateway sends one of the following commands: "Get File" for transferring data files or "Get Photo" for transferring photos. The collar replies with a "File Info" frame containing information about the name and size of the file, followed by eventually multiple packets to the gateway ("File Data"). After the data transfer is complete, the gateway sends the "Delete File" command to delete the transferred file, followed by a delete operation, when successful. The data file contains fields about the sensor data, as well as relevant device information such as the battery and timestamp value. The sequence of commands for sending photos follows a similar process, *mutatis mutandis*. The gateway transmits the “Get Photo” command to initiate the transfer of an image. Subsequently, the collar transmits a “Photo Info” frame to the gateway, which contains the name and size of the photo to be sent. After sending this information, several “Photo Data” frames are sent with the photo data. Once the transfer of the photo data has been completed, the gateway transmits a command to the device to delete the photo, which is acknowledged in case of success.

IV. SYSTEM EVALUATION

In the prototype implementation collar is based on an nRF52833 System on Chip from Nordic Semiconductor featuring an ARM Cortex-M4 at 64 MHz and a Bluetooth 5.4 module. The collar also has a 3-axis accelerometer that is used to monitor the animal’s behavior. The camera is a Arducam Mega 5MP with a Serial Peripheral Interface, 5 MP maximum resolution, auto-focus, and power supply of 3.3 V or 5V. The images are stored in compressed JPG format and with UXGA resolution (1280x720 pixels). Based on the prototype, a few tests were carried out to show the feasibility of the approach and obtain preliminary performance data.

A. Storage tests

Table I presents the total time taken to capture a set of images in different conditions, including illumination and vegetable species. The acquisition time varies with the image contents, from 408 kB to 742 kB. This is expected as the image format used to store data uses compression to reduce the size and compression algorithms depend on spatial redundancy which, in turn, depend on the image and on the illumination. In the case of this test, it was observed that photos with poor lighting and blur have a shorter capture time and size compared to photos with good lighting and good detail, since they contain a higher spatial redundancy.

TABLE I. TIMES AND SIZES OBTAINED FOR DIFFERENT PHOTO SIZES

Photo Number	Total Time (s)	Photo Size (kB)
1	7.9	408
2	8.2	423
3	8.6	413
4	9.9	516
5	10.6	554
6	11.4	596
7	12.3	644
8	13.3	704
9	13.5	706
10	13.9	721
11	14.2	736
12	14.8	742

B. Communications test restults

Table II presents the transfer times of the images to the gateway, with the collar positioned at three distinct distances from the gateway. For the same set of images, the collar was positioned at distances of 5 meters, 15 meters and 25 meters. The images employed in this experiment exhibited a range of file sizes, from 107.6 kB to 761.9 kB. Table III reveals that the time required to transmit images increases in direct proportion to the distance between the collar and the gateway. The most notable alteration was observed between distances of 15 and 25 meters. This is attributed to the placement of the collar in an alternative room, which contained metallic objects, potentially influencing the connectivity between the two devices.

TABLE II. TIME TO TRANSFER AT DIFFERENT DISTANCES

Photo Size (kB)	Distance between collar and gateway		
	5 meters	*15 meters*	*25 meters*
107.6	10s	25s	2m3s
244.8	23s	59s	4m1s
280.6	26s	1m2s	4m42s
392.2	37s	1m34s	6m47s
432.2	40s	1m35s	6m29s
534.6	49s	1m59s	6m47s
638	1m	2m33s	7m51s
761.9	1m13s	2m58s	8m44s

Table III presents the results of an experiment conducted to determine the influence of an increased number of collars on the photo transfer time. The objective was to assess whether connecting five collars, which is the maximum number that can be connected and transferred to the gateway, would affect the transfer time. The four additional collars that were connected to the gateway only contained data files. The four collars were distributed throughout the test environment, with the test collar maintained in position at distance two (15 meters).

TABLE III. TIME TO TRANSFER TO DIFFERENT COLLARS CONNECTED TO THE GATEWAY

Photo Size (kB)	Collars connected to the gateway	
	1 Collar	*5 Collars*
107.6	25s	1m12s
244.8	59s	2m55s
280.6	1m2s	3m45s
392.2	1m34s	4m25s
432.2	1m35s	4m58s
534.6	1m59s	5m27s
638	2m33s	7m20s
761.9	2m58s	7m52s

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Analyzing Table III, it becomes evident that the time required to transmit images increases when the gateway is connected to five collars. For example, for a size of 432.2 kB the time elapsed increase from 1 minute and 35 seconds to 4 minutes and 58 seconds, which corresponds to an increase of 3m23s. This is due to the gateway having to divide its bandwidth and processing capacity between 5 devices, slowing down the transfer time for each one. As the gateway is only capable of connecting to a maximum of five collars at any given time, the presence of either ten or five collars does not affect the data transfer times. These times can be used to estimate the number of photos that can be transferred per hour. Assuming that the photos are approximately 535 kB in size, and that there are five or more collars on the sheepfold with five of them connected to the gateway, 11 photos can be transferred per hour. In the most unfavorable scenario, if the photos have an average size of 762 kB, only seven photos can be transferred per hour.

C. Photo results

Figure 3. presents the collar designed to integrate the camera and the rest of the system.

Figure 3. Collar detail.

Figure 4. Photo captured by the camera attached to the collar.

Figure 4. presents a picture taken with the camera while the sheep were feeding. The image shows that the photos have been taken with sufficient quality to allow the floral species in the photos to be identified. Depending on the lighting in the scene, the camera tends to focus on the best lit areas, sometimes leaving other areas darker or lighter.

V. Conclusions

In this paper, we have addressed the limitations of current animal monitoring systems by developing an innovative device that integrates machine learning-based posture detection to autonomously capture images of pastures during sheep feeding activities. Our approach minimizes redundant data collection and reduces the dependency on manual intervention, thus improving efficiency and extending the operational autonomy of the monitoring system. The implementation of the image transfer protocol between the collar and the gateway ensures efficient and reliable data transmission. By sending only relevant data and photos, and automating the deletion process post-transfer, the system significantly conserves memory and energy resources. The preliminary results show our approach's feasibility, highlighting its potential to enhance pasture management and animal health monitoring on a broader scale.

Future work will focus on implementing the full system and refining the ML algorithms for improving accuracy, expanding the system's applicability to other animal species, and further automating the data analysis process to provide real-time insights for farmers.

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