https://doi.org/10.17221/90/2024-CJAS

Approach to creating an intelligent system for free-range livestock farming

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Citation: Malinova R., Malinov P., Valchev E., Glushkova T. (2024): Approach to creating an intelligent system for free-range livestock farming. Czech J. Anim. Sci., 69: 389–399.

Abstract: The development of intelligent systems for the tracking of free-range livestock is a challenge to both information and communication technology (ICT) scientists and those in the animal sciences. Cyber-physical systems make it possible to track and control processes involving intelligent objects from the physical and virtual worlds. In the case of free-range grazing, it is necessary to manage processes in two domains – that of the intelligent pasture management and that of the animals. Due to the differences in the conditions of different types of pastures – plain or high land and the characteristics of the cattle breeds, ready-made models cannot be used, but it is necessary to build a specific multi-aspect model for the behaviour and life cycle of cows. Our team organised their research on cows from two different breeds (Rhodope Shorthorn Cattle and Bulgarian Rhodope Cattle) raised in similar technologies, grazed on two different types of pasture. The aim of the study is to develop a comprehensive model for determining cattle behavioural activities on pastures using sensor groups, by incorporating physical observations and appropriate statistical models.

Keywords: Cyber-Physical Systems (CPS); intelligent agriculture; intelligent livestock; intelligent pasture

In the process of modern development, ecological intensification in ruminant farming has emerged as extremely important, given the demand for healthy food and at the same time the need to minimize negative impacts on the environment (Caram et al. 2023). Over the next 30 years, the demand for quality animal feed is expected to increase by 38% as a result of the population growth and increased financial income (Komarek et al. 2021). Parallel to this trend is the need to reduce global methane (CH_4) emissions by at least 30% by 2030, especially considering the fact that agriculture and livestock generate around 25% of CH_4 emissions (International Energy Agency; IEA 2021).

There are studies and initiatives that assess the potential to reduce greenhouse gas emissions from livestock production on a global scale (Castonguay et al. 2023; Thornton et al. 2023). Improving and optimising the bioeconomic efficiency of grazing systems by improving animal nutrition, genetics, livestock health, and management practices (Cazzuli et al. 2023; Serrano 2023) are major tasks

Supported by the National Scientific Program "Intelligent Animal Husbandry", approved by Decision No. 866/26.

https://doi.org/10.17221/90/2024-CJAS

for the scientific community at the current stage of development. The use of modern information and communication technologies can significantly solve the problems of monitoring, analysis, and overall management of these processes.

One of the basic trends in the modern stage of development of the digital society is the transformation of existing traditional systems into intelligent cyber-physical systems (CPS) that interact with the real physical world through the Internet of things (IoT). The parallel and dynamic interaction between the physical, social, and virtual worlds determines the need to build a cyber-physical-social system (CPSS) which takes into account the human factor during the operation and management of the system (Zhang et al. 2018).

We used the key features of the reference CPSS architecture by building a prototype of a cyber-physical system for monitoring and managing the behaviour of free-range cows on pastures.

The development of appropriate intelligent systems requires the creation and implementation of models that account for and classify cow behaviour. Liu et al. (2023) presented the automatic classification of 7 cow behaviour patterns [rub scratching (leg), ruminating-lying, lying, feeding, self-licking, rub scratching (neck), and social (licking)] with an inertial measurement unit (IMU) through a fully convolutional network (FCN) algorithm. Since the monitoring of cattle behaviour is fundamental to the early detection of animal health and welfare problems, a study on the living and feeding behaviour of each individual animal is presented in the study Pavlovic et al. 2021. They used a convolutional neural network (CNN) to classify the behavioural states of cattle using data generated by neck-mounted accelerometer collars. In the same direction is the research of Bloch et al. (2023), whose aims are to develop and analyse a classification model based on CNN and transfer learning for automated recognition of the feeding behaviour of dairy cows.

Despite the accumulated worldwide experience in the creation of intelligent cattle breeding systems (Greenwood et al. 2021; Golinski et al. 2022), the models for the behaviour and development of animals in the ecological environment of pasture breeding (Schmeling et al. 2021) are too few, due to the specificity of the environmental conditions. In Bulgaria, given the mountainous and semi-mountainous topography, grazing cows is a traditional business with opportunities for effective future development.

The scientific research aims to establish a model for tracking the development of both the herd as a whole and each individual animal. Security, well-being, and risk management (Arshad et al. 2023) require the use of intelligent components in the cyber-physical space and mechanisms for accurate analysis and rapid response of farmers when necessary. While building the model, we use an iterative approach consisting of the following steps:

Building a sensor IoT configuration; creation of a suitable and animal-friendly prototype of a sensor collar; building an appropriate network for real-time data transmission; creation of a system for processing, storage, and analysis of dynamically incoming data; normalisation of the data and construction of a hypothesis about the behaviour of the animals based on the received data; conducting real observations by farmers and collaborators and adjusting the model.

To date, we have implemented three successive iterations of this model, with each subsequent iteration refining and upgrading the hardware and software developments in all phases. As a result, the built model becomes more and more accurate, reliable, and predictable, which we establish from the control observations of experts observing the real behaviour of cows on the test pastures in the last two phases of the presented iterative approach.

Cyber-physical systems (Dumitrache et al. 2017) make it possible to track dynamically changing conditions and control processes involving intelligent objects from the physical and virtual worlds. Based on the reference architecture of the virtual-physical space (ViPS) Stoyanov et al. (2018) developed in the DeLC Laboratory at Plovdiv University "Paisii Hilendarski", they created an adapted software architecture of the cyber-physical space serving the purposes of grazing cattle. In the conditions of free-ranging ecological livestock, it is necessary to manage the processes in two areas: that of the intelligent pasture management and that of the animals. Valchev et al. (2022) presented an approach to building such an intelligent cyber-physical system in which infrastructure networks of static pasture IoT and dynamic livestock IoT interact. The received data is processed at several levels – sensor, local (in fog), and server (cloud) levels, and conclusions are made about the behaviour and life processes of animals. The main task of personal assistants to farmers is to provide information

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in a user-friendly form and enable remote, fast, and adequate decision-making.

Modelling the behaviour of cattle reared under pasture conditions depends on many factors such as the type of pasture, the breed of cows, and the natural and climatic features of the area. Unlike the controlled environment of cow farms, free-range farming requires managing dynamic changes in the physical environment, which makes it difficult to adapt ready-made tested models of animal behaviour. This motivated our team to build a specific multi-aspect model for the behaviour and life cycle of cows raised on different types of pastures in the climate-geographic features of Bulgaria. We conducted our research on cows of two different breeds (Rhodope Shorthorn Cattle and Bulgarian Rhodope Cattle), reared by similar technologies on two different types of pasture − plain and highland. The aim of the study is to develop a comprehensive model for determining cattle behavioural activities on pastures using sensor groups, by incorporating physical observation and appropriate statistical models.

MATERIAL AND METHODS

The system development methods are divided into four main phases. The first phase is the construction of the infrastructure model and software architecture of the intelligent space for cattle grazing. The construction of the sensor groups and sensor devices and the creation of the local infrastructure for data collection belong to the second phase of the construction of the intelligent environment. The information about the built infrastructure is presented in two different types of pastures: a training pasture of the Agricultural University of Plovdiv and a high-mountain pasture in the region of the city of Momchilgrad (in the Rhodope Mountains).

The third phase is the development of the architecture of the virtual operations centre (VOC; Pencho Malinov; Plovdiv University, Bulgaria), which includes the software and presentation layers from the infrastructure model of the developed intelligent space.

The last, fourth phase of the system implementation is analysing the data from the dynamic monitoring of the cows and detecting statistical dependencies between real physical observations and sensor data by using two implemented prototypes of sensor groups.

Methodology and infrastructure model of the system

The overall infrastructure of the system is based on a multilayered implementation model and comprehensive integration between individual layers. Due to the complexity of the project and the system, we relied on the optimal infrastructure and multilayer differentiated segmentation of the overall system as follows: Sensors and sensor groups; sensor network; infrastructural connectivity between the sensor network and functional servers; server layer for primary storage of information; server layer for application databases (including relational and non-relational databases); data processing and analysis layer (including systems and methods for analysis, processing, machine learning – ML, and artificial intelligence – AI); applied functional layer for data systematisation; client layer for visualisation of the information in a systematised form.

In order to ensure higher levels of technological granularity, we divided the project into three main components:

Static and dynamic sensors; portable and infrastructure environment; software provisioning and implementation of AI and ML.

Figure 1 demonstrates the main and the nested layers in the overall concept and working methodology of the project. The next part presents the three main components of the developed system.

Sensors and sensor groups

At the lowest level, the sensor groups are applied. Each animal has a sensor device with a collection of different sensors. The sensor device is attached to the animal by means of a leash that does not disturb or interfere with the animal's normal behaviour. The physical sensors with which we test the model are acceleration sensor (measurement accuracy ± 0.1 g), angular deviation sensor (measurement accuracy ± 0.5 °), special two-dimensional activity sensor (sensors Fullamp1 and Fullamp2), and localization sensor (measurement accuracy ± 10 m). Six virtual sensors were developed based on the angular deviation sensor. Each of them measures the number of measurements of the physical sensor in a specific range for a given time (2 minutes). The angular deviation ranges are: –90 ° to –70 ° (Full9070 sensor); –69 ° to –50 ° (Full7050 sensor); –49 ° to –30 °

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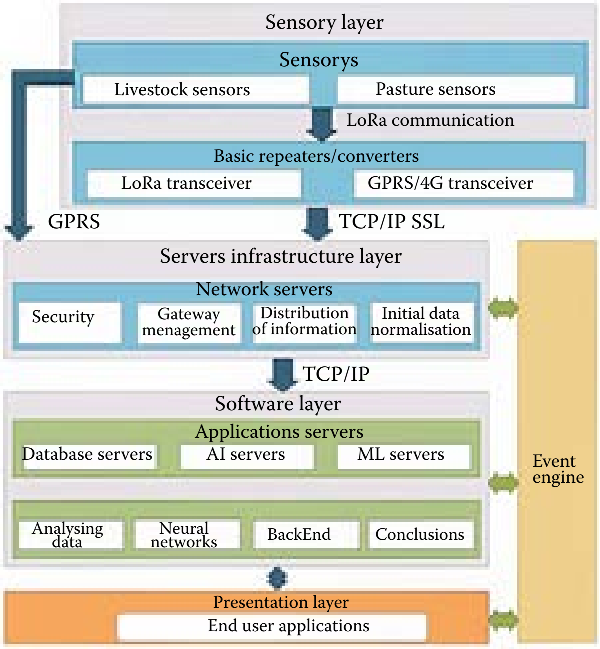

Figure 1. Infrastructure model and system software architecture

AI = artificial intelligence; GPRS = general packet radio service; IP = internet protocol; LoRa = long range; ML = machine learning; SSL = secure sockets layer; TCP = transmission control protocol

(Full5030 sensor); –29 ° to –10 ° (Full3010 sensor); –9 ° to 10 ° (Full1010 sensor); 11 ° to 90 ° (Full1090 sensor). The angular deviation sensor generates measurement results at every half a second.

Two variants of sensor devices are included in the study: prototype 1 (Pr1) and prototype 2 (Pr2). Pr1 includes 8 types of activity sensors and GPS. Using the GPS data from two consecutive transactions, the distance travelled in a straight line is calculated. Pr2 is significantly simplified and includes only three activity sensors. Data from both sensor systems is received at an interval of 2 minutes.

The system, including the software, has been developed so that with minimal effort additional sensors can be included to monitor the condition of the pasture.

The use of both types of sensors, as well as the synthesis of their parameters, has the potential to generate a complete picture of the behavioural characteristics of individual animals and herd habits. In the sensors themselves, processes of primary normalization of the received data are carried out by means of various mathematical algorithms, helping to draw primary conclusions and minimise the volume of sent information.

For the stable and long-term operation of the sensors, it was necessary to carry out several studies and try out different combinations of sensors and mathematical algorithms. The results were obtained after more than 15 different models and combinations of software and hardware parameters. Our goal is to achieve the highest percentage of truthfulness and relevance of information.

Transfer and infrastructure environment and server layers

In parallel to the sensor layer, we also performed the analysis and research in the field of the transport and server environment of the overall project. Work on the primary three layers was carried out in parallel, without hindering or delaying the separate work of the teams working on separate technologies and methodologies.

The main transmission technology used by the project is long range (LoRa) (Marais et al. 2017). It provides the coverage of up to 10 km^2 with one central station, as well as a linear increase in the range without limitations by adding additional ones. In the second place, we used the general packet radio service (GPSR) communication, which has more disadvantages, but also some main advantages. This type is suitable for smaller herds, but the value increases and obstacles arise regarding the coverage of GPRS communication.

Attached, we have selected open frequencies for free use as follows: 868 Mhz for Europe and 433 Mhz for other countries with different regulations. The frequency range conforms to local state broadcasting regulations. The second technology is GPRS – 850/900/1800/1900 MHz.

Development of the virtual operations centre and results

The main module in the system is the VOC. It includes the software and presentation layers from the infrastructure model. The architecture of VOC is presented in Figure 2 and it contains the following set of components and services:

• Farm manager – the component provides services for animals and farm management. Animal management incudes animal health services, pedigree, medical records, etc. The farm management

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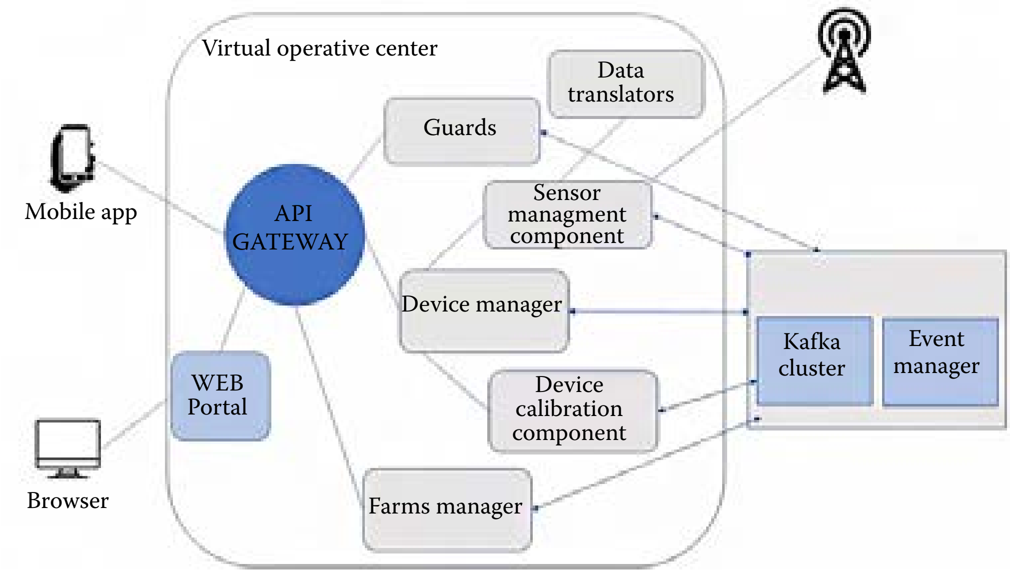

Figure 2. Architecture of the virtual operations centre

services include management of pastures, employee management, feed management, medicine management, etc.

• Devices manager – The component provides a set of services to declare new device configurations with a specific set of sensors. The registration of the devices requires a relation with a given configuration. The component also provides services for device activation which requires a connection with a concrete animal or coordinates on a farm pasture (Figure 3).

• Sensor management component – the component is responsible for registering and managing sensor information.

• Device calibration component – In order to be able to monitor the behaviour of the animals, it is necessary to categorise the data collected by the devices based on a given template. For each type of device, due to the specificity of the sensors that make it up, it is necessary to develop a specific template to calibrate the device. The process of creating, storing, and applying the templates is managed by the cevice calibration component. Calibration involves observations of the animal behaviour both through the devices and direct observations. When receiving data from the device, it is linked to the result of the direct observation. Subsequently, through the statistical analysis of the data, the template itself is created.

• Data translators – the component is responsible for the normalisation of the device raw data.

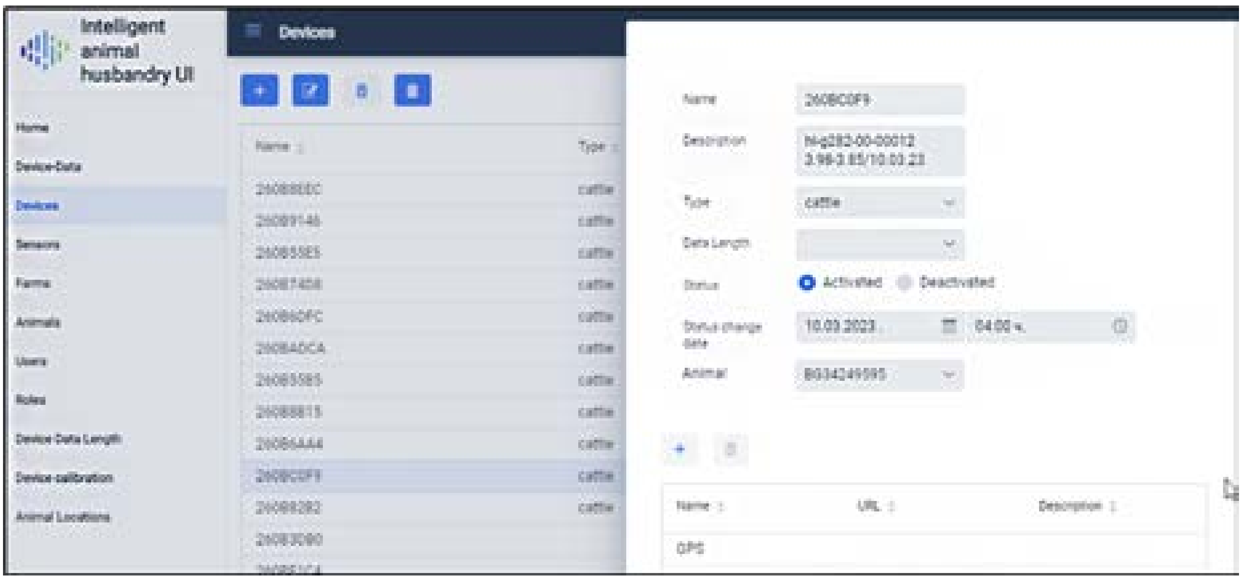

Figure 3. Virtual operations centre – edit device screen

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• Guards – the component provides a set of services related to the safety of animals, such as leaving the perimeter of the pasture, immobility for a certain period, lagging the herd, etc.

In the process of developing and testing the prototypes, we focused on two pastures for ecologically sound cow breeding: a cow farm and pasture affiliated to the educational experimental farm of the Agricultural University Plovdiv (AU); a mountain farm and pasture with the difficult-to-access terrain ear the town of Momchilgrad (in the region of the southeastern part of the Rhodope Mountains).

Studies are currently conducted related to the stability of the connection of the sensor devices with the VOC. In this respect, trials are conducted in parallel at the two farms, with autochthonous and local breeds of cows. One farm is in a mountainous area – in the difficult terrain (Figure 4), and the other one is near to Plovdiv in the "Thracian lowland" in the flat terrain (Figure 5.). The animals on both farms are in the pastures far from the farms for most of the year, which is why it is impossible to use WiFi. Part of the research aimed to collect enough data to evaluate the capabilities of the LoRa network in different terrains. After testing the reliability of the network, the specification of the prototype sensor system, the robustness and safety of the physical sensor devices, the animals on these two farms were subjected to studies of their behaviour under pasture conditions.

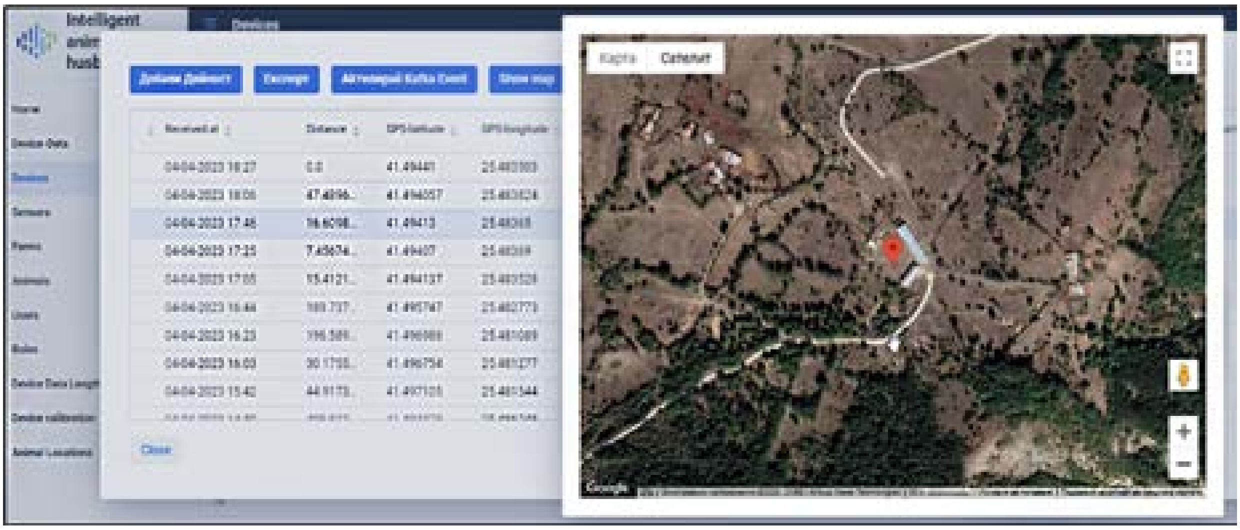

Figure 4. Virtual operations centre – a record of the animal activity on pasture in a mountainous area

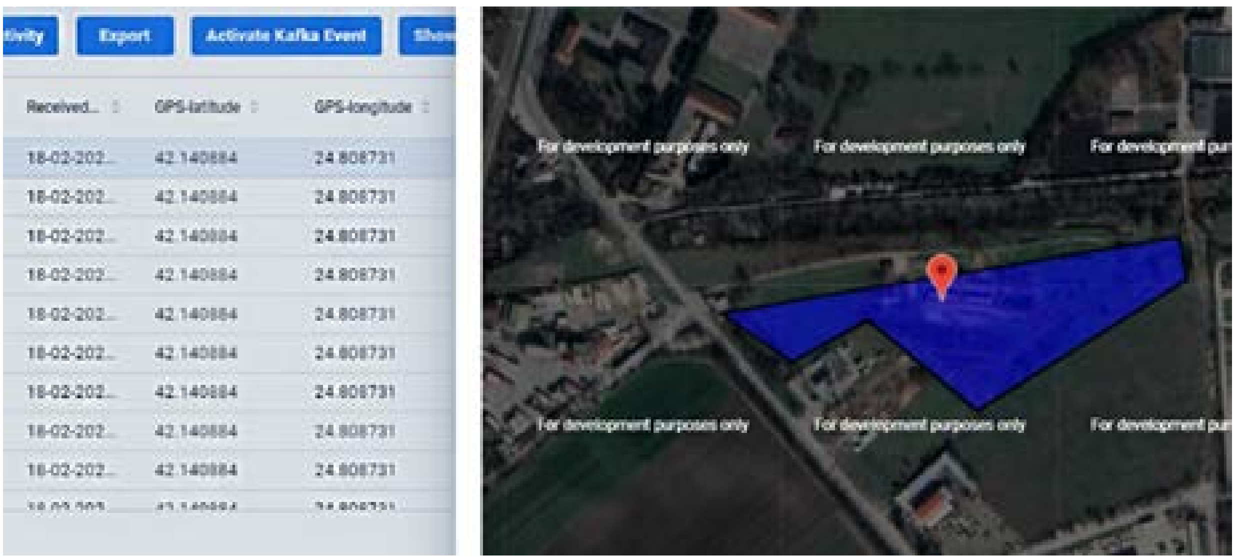

Figure 5. Virtual operations centre – a record of the animal activity on pasture in the Thracian lowland

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RESULTS AND DISCUSSION

A study was conducted on the functionality of two prototype sensor devices, including two sets of different types of sensors. Both types of devices (Figure 6) include sensors for measuring the animal activity and a gyroscope, as in Pr1 a GPS sensor is also installed. Thanks to it, the distance travelled in a straight line by the animal within two consecutive measurements is also calculated.

In Pr1, several basic types of sensors are used. The geolocalisation uses a GPS sensor that positions the animal and measures the distances travelled per unit of time, as well as performs various types of behavioural analyses relative to grazing areas. We also use sensors to position the animal's neck by affecting 3 spatial planes. The data allow us to measure in detail the overall behaviour of the animal by determining the positioning of the head and in combination with the other data – the overall behavioural pattern. The third group of sensors consists of two-dimensional activity sensors. They allow the completion of the entire data set and the digital expression of the animal's behaviour and activity. The set of the three main groups of sensors is primarily analysed and combined at the sensor level, which is subsequently processed in detail in the software layer.

Figure 6 Two different prototypes of sensor devices

Prototypes of the sensor devices were mounted *via* appropriately modelled collars on the animal necks. Sensor data are acquired at 2-minute intervals. Physical observations were also performed to calibrate the animal activities *vs* the sensor data. With each transaction of data from the sensors, by a specially built component of the system, a request is generated to the observer to enter a specific activity at the time of receiving the data (Figure 7). The system allows several activities to be selected at the same time. The corresponding behavioural activity is recorded directly in the database with the sensor data it applies to. The connection of the real activities of the animals with the relevant sensory data serves to verify the developed model. The physically observed and reported responses of the animals for the individual types of devices are as follows: 115 for Pr1 and 274 for Pr2.

In the calibration software, the sensors have options for the following activities: walking, standing, sleeping, grazing, urinating, standing to be mounted, running, laying, drinking, defecating, ruminating, mounting. The behavioural observer is prompted by the calibration component to select one or more of the activities that the animal has performed in the previous two-minute period. Due to the short period of physical observation of the behaviour for some of the activities, not enough data was collected to be included in the statistical analysis.

To analyse the relationship between the sensor data and the real behavioural responses at the given moment, a multivariate linear model (Equation 1)

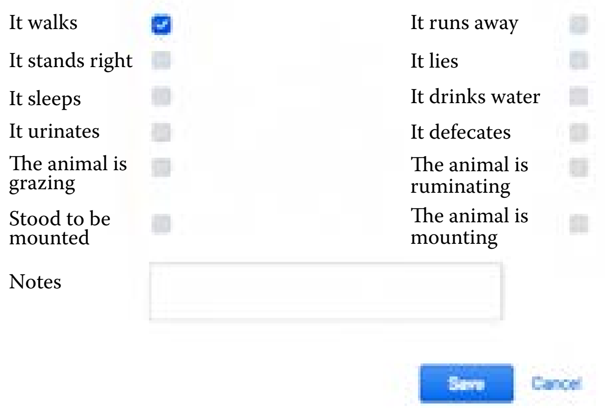

Figure 7. Software component for calibrating the model

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was used, by which we accounted for the influence of the activity as a factor on the data obtained from each of the sensors. The statistical model is used separately for data of each prototype.

$$Y_{ij} = \mu + D_i + e_{ij} \tag{1}$$

where:

Y_{ij} – an observation vector (an activity the animal performs);

μ – a general average constant;

D_i – the fixed effect of the i^{th} activity (Pr1: walking, running, grazing, grazing and seeking pasture grass, grazing leaves from woody vegetation; Pr2 fighting, walking, mounting, lying down, lying down and rumination, grazing, standing and standing and rumination);

e_{ij} – the residual variance.

The data were processed statistically with the statistical software SPSS (v21; IBM, New York, USA).

From Table 1 it is clear that the activity carried out at the time of receiving the data from the sensors significantly affects most of the values. We have reported an insignificant influence only for two of the twelve sensors used – Fullamp2 (activity sensor) and Full9070 (accelerometer), located in Pr1, for which we have twice as little data.

These results give us a reason to accept that with the accumulation of a sufficiently large array of data collected in parallel by the sensors and visual reporting of the animal activity, we can successfully use the multifactor analysis of variance (ANOVA) as a statistical tool to verify the adequacy of the sensors included in the devices for tracking the animal behaviour.

Table 1. Influence of the activity performed at the time of the observation on the values of the sensors, *F*-test and confidence level

Prototype devices	Sensors	*F*-value	Significance
Prototype 1	Fullamp2 (rad/T)	2.01	0.098
	Fullamp1 (rad/T)	52.3	0.000
	Full9070 (N/T)	2.19	0.075
	Full7050 (N/T)	5.50	0.000
	Full5030 (N/T)	5.15	0.001
	Full3010 (N/T)	5.03	0.001
	Full1010 (N/T)	12.4	0.000
	Full1090 (N/T)	10.1	0.000
	Distance (m)	75.4	0.000
Prototype 2	Activity (Hz/T)	11.3	0.000
	axX	43.1	0.000
	axY	20.9	0.000

N = number of measurements; T = time period

The 2-min period in which the data from the sensors is received is completely sufficient to perform the system calibration.

Table 2 presents the results of the study conducted on Pr1. It shows that for each activity the average values of the sensor data differ significantly. On the other hand, a unique combination of indicators can be observed for different activities. For example, the activities "grazing" and "grazing and movement in search of pasture" appear close, but it is noticed that the distance reported based on the GPS sensor differs significantly: 27.01 ± 2.662 m and 35.62 ± 6.137 m, respectively ($P < 0.001$). More significant differences in these two activities were also observed between the indicators of Fullamp1.

In two of the sensors used, Fullamp2 and Full9070, there is a wide variation and a large statistical error due to an insufficient amount of data collected from physical observations of behaviour. In this regard, it is necessary to conduct a larger number of observations to cover more activities and define statistically reliable intervals of variation for each sensor during specific activities, so that in a subsequent stage, activity definition can be done through software.

In the composition of Pr2, three virtual sensors are included: for measuring activity, acceleration sensor and angular deviation sensor along the X and Y axes. Despite their small set, from Figure 8 it is clear that they provide sufficiently reliable information to separate different activities. With this prototype, we have managed to collect a much larger volume of data for more types of activities, with all activities differing notably and statistically significantly ($P < 0.001$). Accelerometers are widely used to measure walking in cattle. According to Kamminga et al. (2017), collar tags equipped with accelerometers accurately classify walking behaviours. Umstatter et al. (2008) demonstrated that accelerometers could reliably differentiate between lying and standing postures. This is crucial for monitoring cow comfort and welfare, as excessive or insufficient lying time can indicate health issues.

The biggest differences for all types of activities are observed in relation to the activity sensor.

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Table 2. Average values of data obtained from prototype 1

Sensor	Walking		Running		Grazing		Grazing and seeking pasture grass		Grazing leaves from woody vegetation	
	mean	± SE	mean	± SE	mean	± SE	mean	± SE	mean	± SE
Fullamp2[1] (rad/T)	232.0	44.66	158.0	99.9	238.8	10.8	185.2	25.0	132.5	49.9
Fullamp1[1] (rad/T)	56.0	9.27	296.0	20.7	18.6	2.25	26.9	5.18	70.3	10.4
Full9070[2] (N/T)	8.00	3.21	2.00	7.17	12.8	0.78	11.2	1.79	4.75	3.59
Full7050[2] (N/T)	37.8	8.77	3.00	19.6	52.8	2.13	56.7	4.90	17.0	9.80
Full5030[2] (N/T)	27.4	5.39	6.00	12.0	37.6	1.31	34.6	3.01	16.7	6.02
Full3010[2] (N/T)	25.0	4.06	39.0	9.08	11.6	0.98	10.2	2.27	14.7	4.54
Full1010[2] (N/T)	12.4	2.94	35.0	6.57	5.14	0.712	7.37	1.64	22.2	3.28
Full1090[2] (N/T)	12.2	7.40	41.0	16.5	5.75	1.79	5.62	4.14	56.5	8.27
Distance (m)	57.4	11.0	452.2	24.5	27.0	2.66	35.6	6.137	38.7	12.3

[1]Number of measurements within a specific angular range per 2-min time period; [2]Radians per 2-min time period
N = number of measurements; SE = standard error; T = time period

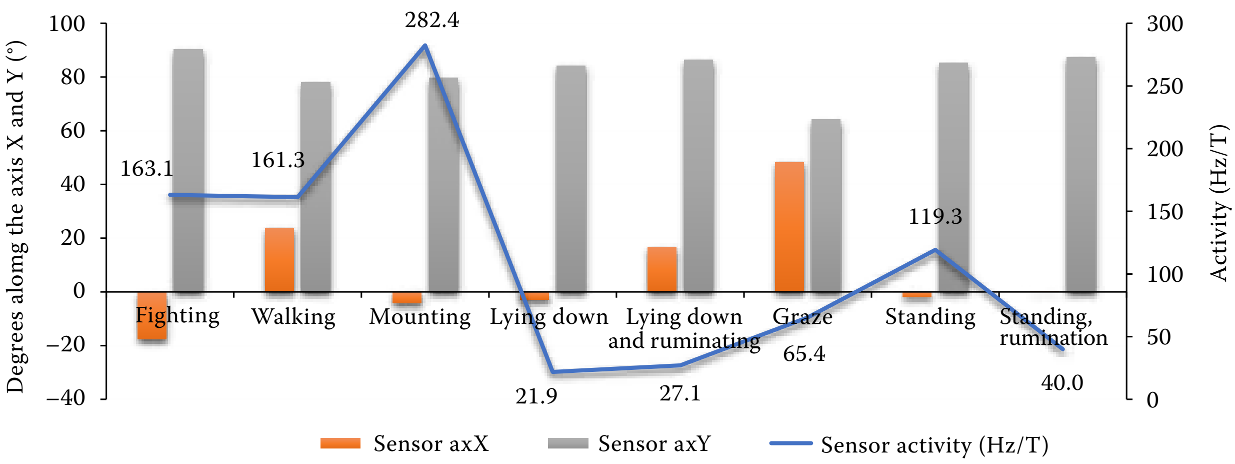

Figure 8. Influence of activities on the sensor performance in prototype 2

The deviation along X is in negative values, the most significantly when mounting and fighting. When walking, lying down and rumination as well as during grazing, this deviation along X has positive values. For all other activities, the values are close to zero. Since the collar of Pr2 is equipped with a weight suspended at its lower end, the gyroscope does not almost change its position along Y, and/or the Y measurements for all activities have very close values – from 64.2 ± 1.45 to 90.2 ± 4.70 ($P < 0.001$). Similarly to Pr1, each activity is characterised by a unique combination of average values from the sensors. With subsequent software determination of the limits of variation of each indicator for the relevant activity and the specific combination of all of them, it would allow us to successfully differentiate and recognize the relevant activity. This will allow data from the developed system to come in the form of activities, such as time spent grazing, resting, walking, etc., all the characteristics of the animal behaviour by which to judge its well-being and indirectly the lack or presence of sufficient pasture grass.

CONCLUSION

Multivariate analysis of variance could be successfully applied as a statistical tool to verify the adequacy of the sensors included in the devices for tracking the animal behaviour. In addition, it can be used to define reference values and combinations of sensory data with which to account for the activity and behavioural patterns of each animal.

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The results of the multifactor analysis of variance give us a reason to accept that with the accumulation of a sufficiently large array of data collected in parallel by the sensors and visual reporting of the animal activity, we can successfully use the multifactor analysis as a statistical tool to verify the adequacy of the sensors included in the devices for tracking the animal behaviour.

In the composition of Pr2 where three sensors are included, it is sufficient to provide reliable information to separate different activities. With this prototype all activities differed notably and statistically significantly ($P < 0.001$).

The 2-min period in which the data from the sensors is received is completely sufficient to perform the system calibration.

In the future plan with subsequent software determination of the limits of variation of each indicator for the relevant activity and the specific combination of all of them, it would allow us to successfully differentiate and recognize the relevant activity. This will allow data from the developed system to come in the form of activities, such as time spent grazing, resting, walking, etc., all the characteristics of the animal behaviour by which to judge its well-being and indirectly the lack or presence of sufficient pasture grass.

Conflict of interest

The authors declare no conflict of interest.

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Received: June 6, 2024
Accepted: October 6, 2024
Published online: October 31, 2024