MULTIFACTOR ANALYSIS OF BEHAVIORAL PATTERNS IN PASTURE-RAISED LIVESTOCK USING DATA FROM DYNAMIC SENSORS

Evgeni Valchev, Todorka Glushkova, Radka Malinova

Abstract. *In this study, we present a multifactor analysis of the behaviour of free-range grazing cows using data collected from sensors mounted on collars on the animals. GPS, accelerometers, and other dynamic data were used for the automated classification of key behavioural states such as grazing, lying, ruminating, walking, running, and sleeping. By combining spatial and temporal information, as well as movement intensity, an analytical model was developed to assess the condition and welfare of the animals. Formulas for calculating distance travelled, temporal analysis of states, and classification rules based on activity thresholds are presented. Visualizations include time diagrams of behavioural states, GPS tracks, and pie charts of activity distribution. The results demonstrate the potential of sensor technologies for early detection of behavioural deviations, optimization of pasture management, and improvement of animal welfare.*

Key words: Multifactor Analysis, IoT, Sensor Technologies, Behavioral Patterns

Introduction

In the context of modern development, ecological intensification in ruminant livestock farming has emerged as a critical priority, driven by the growing demand for healthy food and the need to minimise negative environmental impacts. Numerous studies and initiatives have assessed the potential for reducing greenhouse gas emissions from livestock production on a global scale.

Improving and optimising the bio economic efficiency of pasture-based systems through enhanced animal nutrition, genetics, livestock health, and management practices are key objectives for the scientific community at this stage of development. The use of advanced information and communication technologies can significantly address challenges related to monitoring, analysis, and overall process management, while also optimising livestock farming by analysing animal behaviour.

One of the major trends in today's digital society is the transformation of traditional systems into intelligent cyber-physical systems that interact with the physical world through the Internet of Things (IoT). The dynamic interplay between physical, social, and virtual environments highlights the need for developing a cyber-physical-social system (CPSS) that incorporates the human factor during system operation and management.

We applied the core principles of the reference CPSS architecture to build a prototype cyber-physical system for monitoring and managing the behaviour of free-ranging cattle on pastures. Developing effective intelligent systems requires creating and implementing models that recognise and classify cattle behaviour. In this study, we explore the classification of six behavioural patterns – grazing, lying, ruminating, walking, running, and sleeping – using AI algorithms. Since monitoring cattle behaviour is essential for early detection of health and welfare issues, the research presents an approach for analysing the life and feeding patterns of individual animals.

For this purpose, we use neck-mounted sensors, sensor networks for data collection, and a multilayer software architecture for processing and analysing incoming data. Despite global progress in developing smart livestock farming systems [1, 2] behavioural models for animals in ecological pasture environments [3] remain scarce due to the complexity of environmental conditions. In Bulgaria, given the mountainous and semi-mountainous terrain, cattle grazing is a traditional practice with strong potential for sustainable future development.

Security, welfare, and risk management [4] require intelligent components in the cyber-physical space and mechanisms for accurate analysis and rapid farmer response when necessary. Our model development follows an iterative approach consisting of the following steps:

- Building an IoT sensor configuration;
- Designing a comfortable sensor collar prototype for animals and establishing a real-time data transmission network.
- Creating a system for processing, storing, and analyzing dynamically incoming data.
- Normalizing data and formulating hypotheses about animal behavior based on collected information.
- Conducting field observations by farmers and collaborators to refine the model.

Cyber-physical systems [5] enable tracking dynamically changing conditions and managing processes involving intelligent objects from both physical and virtual worlds. Modelling cattle behaviours in pasture conditions depends on multiple factors, such as pasture type, cattle breed, and regional natural and climatic characteristics. Unlike controlled farm environments, free-range grazing requires managing dynamic changes in the physical environment, making it difficult to adapt pre-tested behavioural models.

The aim of this study is to test the application of a model for determining cattle behaviour on pastures using sensor arrays, combined with physical observation and appropriate statistical models.

Technologies used for the study

A wide range of software and hardware technologies is utilised to meet the needs of multifactor data analysis. This is because, before analysing the data, it is necessary to collect, systematise, and process it initially. We designed a cyber-physical system (CPS) prototype for monitoring free-ranging cattle behaviour. The iterative development process included:

- Building an IoT sensor configuration and a comfortable sensor collar prototype;
- Establishing a real-time data transmission network.
- Developing a multilayer architecture for data processing, storage, and analysis;
- Normalizing data and formulating behavioural hypotheses.
- Conducting field observations to refine the model.

Behavioural classification was performed using AI algorithms for six activity patterns: grazing, lying, ruminating, walking, running, and sleeping. Data were collected via neck-mounted sensors and sensor networks.

Sensors and sensor groups

At the lowest level, sensor groups are deployed. Each animal is equipped with a sensor device containing a collection of different sensors. The device is attached to the animal using a collar designed not to interfere with its normal behavior (Figure 1). The physical sensors used in the study include an accelerometer, an angular displacement sensor, a two-dimensional activity sensor, and a localization sensor.

Additionally, six virtual sensors were developed based on the angular displacement sensor. Each virtual sensor measures the number of readings from the physical sensor within a specific range over a given time interval. The angular displacement ranges are as follows:

- $-90°$ to $-70°$ (sensor Full9070)

- –69° to –50° (sensor Full7050)
- –49° to –30° (sensor Full5030)
- –29° to –10° (sensor Full3010)
- –9° to 10° (sensor Full1010)
- 11° to 90° (sensor Full1090)

The angular displacement sensor generates measurement results several times per second.

The sensor devices also include eight types of activity sensors and GPS. Using GPS data from two consecutive readings, the straight-line distance traveled is calculated. Within the sensors themselves, primary data normalization processes are performed using various mathematical algorithms. These algorithms help derive preliminary conclusions and reduce the volume of transmitted information.

Figure 1. Sensors' prototypes

Software multilayer architecture for data processing

The overall system infrastructure is based on a multi-layer deployment model with full integration between the individual layers. Due to the complexity of the project and the system, we rely on an optimized infrastructure and a differentiated multi-layer segmentation, structured as follows:

- Sensor layer: sensors and sensor groups.
- Sensor network: connectivity for data collection.
- Infrastructure layer: communication between the sensor network and functional servers.
- Primary storage layer: servers for initial data storage.
- Database layer: application-level databases, including both relational and non-relational systems.

- Data processing and analytics layer: systems and methods for data processing and analysis.
- Application layer: functional components for data organization and systematization.
- Client layer: visualization interface for presenting structured information.

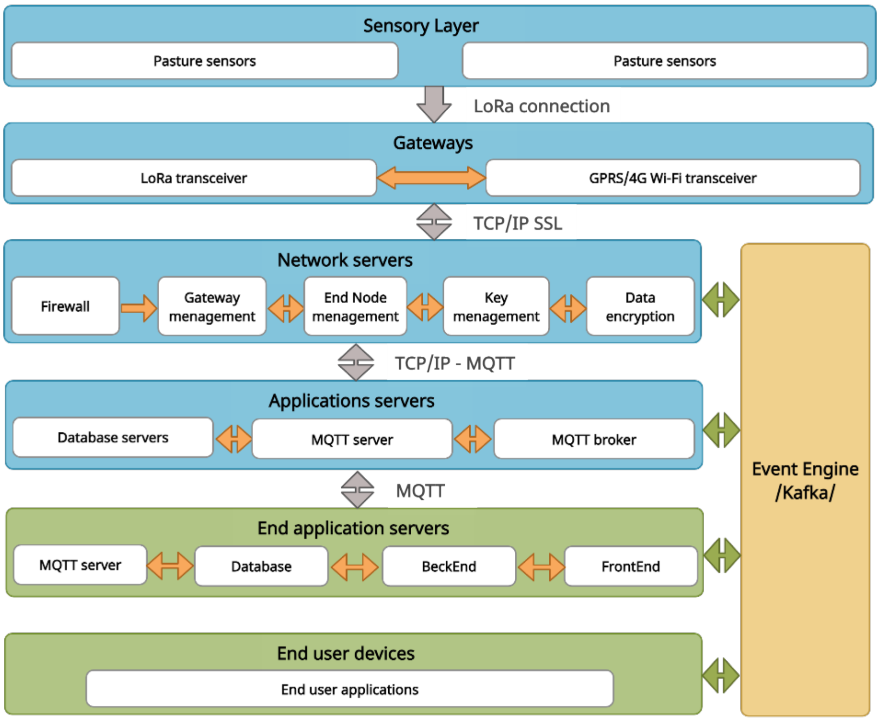


Figure 2. System architecture

The use of multi-layered software architecture significantly helps to conduct comprehensive functional tests and information analysis, which is essential for achieving a positive result of the study.

Data Analysis and Algorithms

To process and interpret sensor data, two algorithmic approaches were applied: Behavioral State Recognition and Anomaly Detection (Figure 3).

Behavioral State Recognition. For automatic classification of behavioral states – grazing, lying, ruminating, walking, running, and sleeping – we employed a machine learning model based on the Random Forest algorithm. Random Forest is an ensemble learning method that combines multiple decision trees for classification or regression. Each tree is trained on a different subset of the data, and the final prediction is obtained through majority voting (classification) or averaging (regression). The input features for this model include:

- Accelerometer readings (X, Y)
- GPS coordinates
- Speed
- Magnetometer indicators

Anomaly Detection. To enable early detection of abnormal behavior, we applied an anomaly detection model based on the Isolation Forest algorithm. Isolation Forest is particularly effective for identifying outliers or unusual patterns in large datasets. The model analyzes time-series activity data to detect atypical changes that may indicate health issues or stress. The input parameters for anomaly detection include:

- Duration of behavioral states
- Movement intensity
- Changes in GPS trajectory

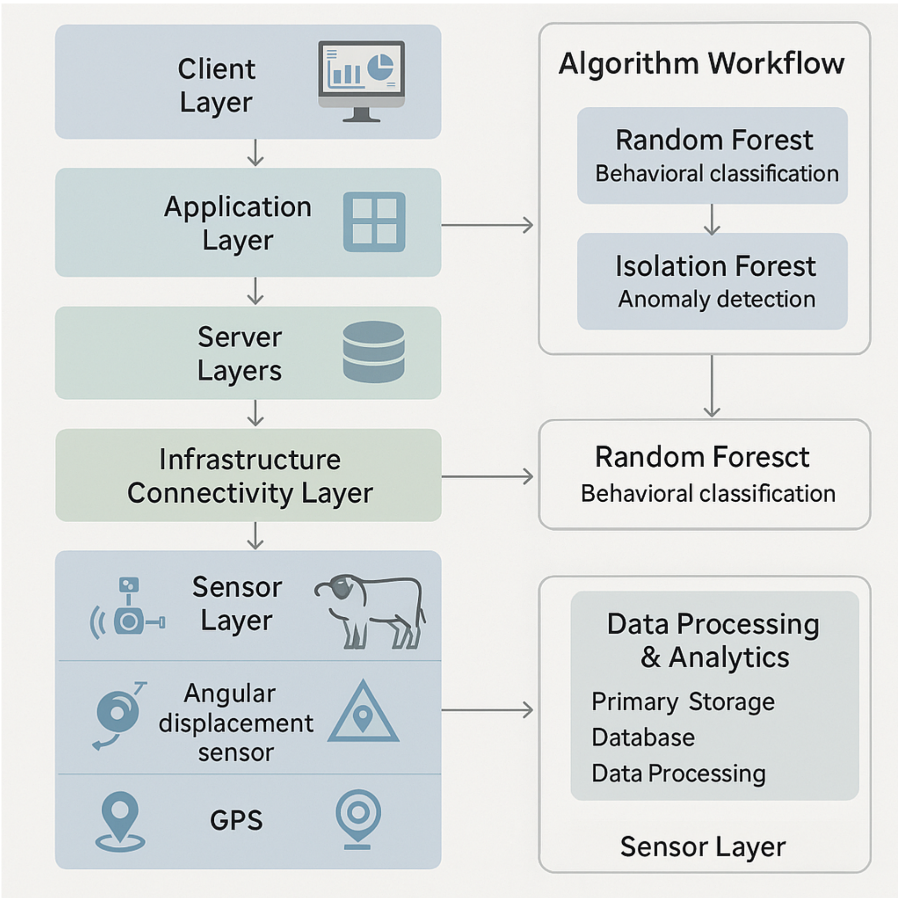
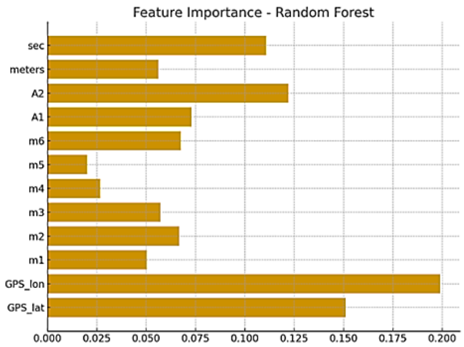


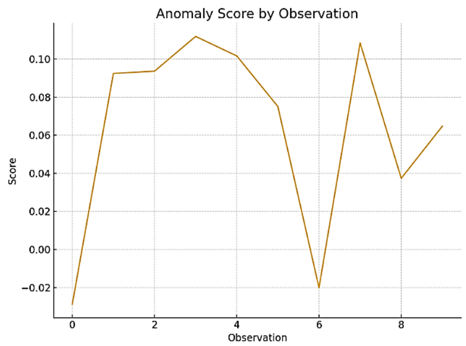
Figure 3. Algorithm Workflow

The table below shows a fragment of the data in a semi-normalized form, over which the algorithms for training and analyzing the model data are applied.

GPS-latitude	GPS-longitude	Received At	-90 / -70	-70 / -50	-50 / -30	-30 / -10	-10 / 10	10 / 90	Activity 1	Activity 2	Meters	Hour	Time in sec.	Descr.
42.142944	24.81004	19-06-2022	0	2	5	61	31	28	104	68	0.00	10:51:48	653.00	Walk
42.14271	24.810001	19-06-2022	14	71	23	8	2	2	34	273	1.51	10:40:55	260.00	Walk
42.142662	24.809963	19-06-2022	13	81	32	10	3	2	36	208	0.32	10:36:35	284.00	Walk
42.142735	24.809097	19-06-2022	8	70	33	11	3	3	36	215	1.55	10:31:51	134.00	Walk
42.142673	24.808655	19-06-2022	10	66	25	8	10	1	46	217	0.85	10:29:37	345.00	Walk
42.144	24.806551	19-06-2022	16	81	26	2	0	2	48	218	#REF!	09:58:10	265.00	pasture
42.144108	24.806168	19-06-2022	12	44	28	24	7	10	88	292	0.95	09:53:45	262.00	Walk
42.144115	24.805283	19-06-2022	0	0	4	5	44	75	39	10	1.51	09:49:23	129.00	Eats
42.14396	24.805233	19-06-2022	8	57	30	11	7	12	59	169	1.00	09:47:14	130.00	Eats
42.14357	24.805347	19-06-2022	1	8	18	19	25	49	94	57	2.52	09:45:04	259.00	Graze
42.14355	24.805962	19-06-2022	2	14	50	34	20	11	64	333	1.06	09:40:45	138.00	graze



(a)



(b)

Figure 4. Algorithm Workflow

The graph (Figure 4a) shows the influence of each variable (GPS, angular movement, Activity 1/2, Meters, Time) on the final classified behavior. The greatest weight is given to Activity 2, Movement range $-90/-70$ and meters. As expected, GPS coordinates have a low influence, since location alone cannot determine the behavior of animals. The graph (Figure 4b) shows the `decision_function()` value for each observation. Points with significantly lower scores (below -0.2) are likely anomalies and can be interpreted as: atypical behavior; lack of movement; sensor error, etc.

Conclusions and future plans

This study demonstrates the feasibility and effectiveness of integrating cyber-physical systems (CPS) with IoT technologies for monitoring and analyzing cattle behavior in pasture-based environments. By employing a multi-layer architecture – encompassing sensor devices, communication networks, data processing servers, and visualization interfaces – the system enables real-time data acquisition and intelligent decision-making.

The use of advanced algorithms, such as Random Forest for behavioral classification and Isolation Forest for anomaly detection, provides accurate identification of activity patterns and early detection of irregularities that may indicate health or welfare issues. This approach addresses the challenges posed by dynamic environmental conditions and supports sustainable livestock management practices. The proposed solution not only enhances animal welfare and farm productivity but also contributes to ecological intensification by optimizing resource use and minimizing environmental impact.

Future work will focus on refining behavioral models, expanding sensor capabilities, and integrating predictive analytics to further improve system performance and adaptability.

Acknowledgments

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