Sensor Network System for Condition Detection of Harmful Animals by Step-by-step Interlocking of Various Sensors

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***Abstract*—In recent years, damage to crops and injuries to humans by harmful birds and animals have increased in areas of Japan. In order to support the coexistence of humans and wildlife, technologies for observing the ecology of wildlife and detecting harmful birds and animals are attracting attention. In our previous study, a method of detecting animals by utilizing a radio beacon has been proposed. In the system, the reception signal strength of radio waves transmitted between radio beacon devices is continuously measured and analyzed to identify the existence of the wildlife near the devices by using machine learning technology. However, the existing method of analyzing the radio wave strength cannot estimate the posture of the animal which can be utilized to identify the detailed behavior of the animals (e.g., the point where feeding behavior was taken) and to understand the situation of damage caused by them in more detail. Therefore, in this study, we propose a new sensor network system that detects the presence of wild animals by analyzing images taken by the thermal camera that can measure the body temperature of the organism day and night. In addition, in order to reduce the power consumption of the entire system that is assumed to be installed in mountain areas where the power supply is difficult, the thermal camera is activated only when the doppler sensor with low power consumption detects the moving object. After that, by analyzing the captured images using a machine learning technology, the system attempts to estimate not only the type and the number but also the posture of the animals.**

***Index Terms*—IoT, wild animals damage prevention, machine learning, doppler sensor, thermal camera**

I. Introduction

In recent years, damage to crops caused by harmful birds and animals (e.g., wild boars, deer) becomes a serious problem. Although the total amount of damage is decreasing year by year, it still exceeds 15 billion yen per year [1]. As an example, Figure 1 shows the total amount of annual damage to crops caused by harmful animals nationwide, as published by the Ministry of Agriculture, Forestry and Fisheries, Japan. In order to reduce the damage to crops caused by such harmful birds and animals, it is necessary to monitor their habitats and the number in real-time and to detect their approaching to the human living areas in advance. However, since it is difficult to prepare electricity in mountainous areas where harmful animals live, a system that consumes little power and can monitor harmful birds and animals for a long time is required. On the other hand, countermeasures to the harmful birds and animals such as the capture and extermination of harmful birds and animals by hunters and the installation of preventive fences have been taken, but require hunters to patrol the condition of the equipment deployed in a wide area which results in high cost.

Therefore, existing studies have developed a system that can automatically detect harmful birds and animals and can confirm their location via the Internet [2] [3]. In the system, images taken by the camera are sent to the cloud on the Internet and are analyzed to detect the wild animals on the images. However, in order to send the images with large data size to the server on the Internet and to detect the wild animals in real-time, a high-speed communication network should be prepared, hence the location where the system can be deployed is limited. In addition, the system should be able to work even at night when the wild animals frequently appear [4].

Therefore, in this study, we propose a new sensor network system that can estimate not only the presence of the wild animals but also their species and posture by analyzing images

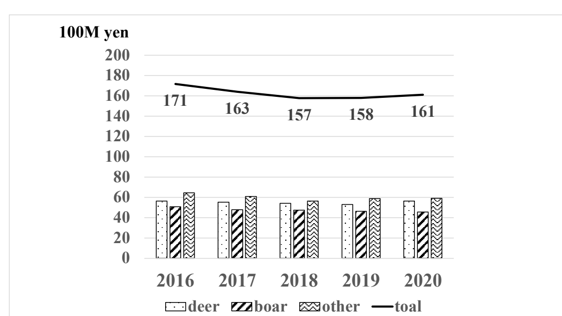

Fig. 1. Total amount of damage to crops caused by harmful animals and birds (from 2016 to 2020).

taken by a thermal camera that can measure the body temperature of living harmful animals day and night. The proposed system adopts an edge computing-based structure where a small computer installed in the field analyzes images taken by the thermal camera to estimate the type and posture of wild animals and sends only the results to the analysis server on the Internet. The system structure can greatly reduce the amount of data sent to the analysis server, making it possible to realize a system that can work even in a mountainous area where the high-speed communication network is not available. In addition, in order to ensure long-term operation even when the camera is installed in mountainous areas where power supply is difficult, the system is configured to activate the thermal camera only when the sensor with low power consumption detects moving objects, thereby realizing overall power saving of the system. Furthermore, this study considers a system for detecting the status of harmful birds and animals using 3D LiDAR which can accurately measure the distance, position, and shape of the target object.

II. Related works and objectives of our study

A. Harmful wildlife detection system utilizing deep learning for radio wave sensing

In previous research by Ogami et al. (2018), a system for detecting harmful animals using radio wave sensing is proposed and developed [5]. The proposed system consists of a device that transmits and receives the radio beacons in multiple frequency bands (2.4 GHz, 920 MHz, and 429 MHz) that have different characteristics of reflection and diffraction between each other. This device is capable of measuring the received signal strength of the radio wave transmitted in multiple frequency bands. By analyzing the measured signal strength of radio waves using machine learning techniques, the system can capture the features related to the size and shape of the wild animals passing between transmitter/receiver devices and can estimate their species and the number. However, this method cannot estimate the posture of the animal that can be used to identify the detailed behavior of the target (e.g., feeding).

B. Damage prevention systems by wild animals using image analysis

In the existing study by Kamesaka et al. (2018), a system for capturing harmful animals using image analysis and machine learning has been proposed [6]. In this proposed system, an RGB camera attached to a cage that lures a group of monkeys takes images and uploads them to the server. And then, the server analyzes the images by utilizing machine learning to determine whether a group of monkeys exist in the image. When a group of monkeys is detected, the person in charge operates the door of the cage via a web browser to capture them. However, since the system uses images with relatively large data size, it requires a high-speed communication network to transmit the data to the server via the Internet to detect the wildlife in real-time. Therefore, the system cannot be used in mountainous areas where wild animals live, but the cellular network such as 4G/LTE is not sufficiently available for the system. Furthermore, since it is difficult to prepare the power supply of the system in the area, the power consumption of the device that detects harmful animals should be reduced so that the system becomes available for a long time.

C. Objectives of our research

In this study, we propose and develop a harmful birds and animals condition detection system that can estimate not only the presence of wild animals but also their species and posture by analyzing images taken by a thermal camera that can measure the body temperature of living harmful animals day and night. The proposed system adopts a system structure of edge computing where images taken by the thermal camera are analyzed on a small computer installed in the field to estimate the type and posture of wild animals. The computer transmits only the result of the analysis to the server on the Internet so that the system can be used even in mountainous areas where a high-speed communication environment is not available. In addition, to ensure that the system can operate for a long time even when it is installed in mountainous areas where power supply is difficult, the system is configured so that the thermal camera with high power consumption is activated only when the doppler sensor with low power consumption detects moving objects.

III. Proposed harmful animal detection system

A. Overview of the proposed system

The overall picture of the system proposed in this study is shown in Fig. 2. As shown in this figure, the proposed system consists of sensor nodes for detecting harmful birds and animals installed in the field and an analysis server deployed on the Internet. In order to save power consumption of the entire system, the sensor node activates the thermal camera for observing the detailed behavior of the target via a relay circuit only when detecting the approach or separation of the object by the doppler sensor. The sensor node then analyzes the image captured by the thermal camera using machine learning technology, estimates the type, number, and posture of the animals present in the image, and transmits the results to the analysis server. The analysis server accumulates the estimation results, visualizes the status of wildlife using a map application, and sends the e-mail to notify users (e.g., hunters, staff of local governments) of the appearance of wildlife.

B. Device/function configuration of the proposed system

In this section, we describe the device and functional configuration of the sensor nodes and the analysis server computing the proposed system.

1) Configuration of sensor nodes: The sensor node is responsible for observing and analyzing data related to the ecology of the wildlife and consists of three devices divided by a function. The first device is a microcontroller that has the function of detecting the approach and departure of wild animals and controlling activation of the second device through relay circuits. In our proposed system, the Arduino

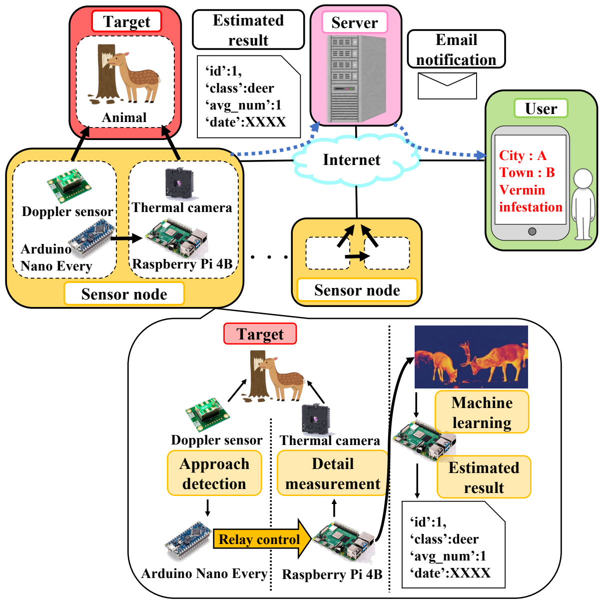

Fig. 2. Overview of proposed system.

Nano Every which is a power-saving microcomputer with a built-in CPU, memory, and an interface to accommodate a variety of sensors are used as the microcontroller. The microcontroller is connected to a doppler sensor for detecting the approach and separation of objects, and a relay circuit for turning on and off the electrical device. A 24 GHz microwave sensor module, NJR4265 J1, is used as the doppler sensor, and a solid-state relay which is a type of non-contact relay is used as the relay circuit. The doppler sensor has a detection distance of 10 m, a detection angle of 70° horizontally and 54° vertically and current consumption of 60 mA.

The second device is a small computer that controls a thermal camera to capture temperature images and analyzes them to identify objects in the images utilizing machine learning. In our proposed system, the small computer is a Raspberry Pi 4B that is a small single-board computer operated on a Linux-based OS and is configured to wake up with 5V power supplied when a relay circuit is connected to the microcontroller is activated. This small computer is connected to a thermal camera for photographing wild animals detected by the doppler sensor. In this study, the thermal camera is the ultra-compact Lepton 3.5 which is capable of capturing temperature images with a resolution of 160×120 pixels and is connected to a small computer via USB using an interface board, PureThermal 2.

The last one is a microcontroller for wireless communication (MAX32630FTHR) that controls the LTE-M (Long Term Evolution for machine-type-communication) module to send analysis results to the analysis server. The MAX32630FTHR is a platform for developing embedded devices that are equipped with a microSD card connector and 6-axis acceleration and gyro sensors. The proposed system assumes the use of LTE-M, a kind of LPWA (Low-Power Wide-Area), which enables wide-area wireless communication with low power consumption, although the communication speed is slow. The LTE-M module of the proposed system is KYW01 which also has the function of positioning using GPS, and is connected to the microcontroller using a dedicated interface board [7]. Through the microcontroller for communication, the sensor data measured by the sensor node is sent to the analysis server on the Internet.

2) Configuration of analysis server: In this system, the analysis server is assumed to be a commercial PC, and a Mac Mini (2018) is used in this study. Here, all the functions of the analysis server are implemented using Python, and Elasticsearch is used as the database to store the data to be analyzed. Elasticsearch is a database supporting a full-text search engine developed by Elastic, which is suitable for real-time analysis of the time-series data. In addition, Kibana is used for a visualization of the data stored on Elasticsearch. The program in the analysis server stores the data received from the sensor node in folders created each date (year/month/day), determines the location of the origin of the data by referring to pre-registered location information of the sensor nodes by the sensor ID recorded in the received data, and stores the received data with the location information of the sensor node in the database in real-time.

C. Linkage method of sensor devices in sensor nodes

In order to achieve overall power saving of the proposed system, the sensor device with high power consumption is activated only when the approaching of wild animals is detected by the sensor device with low power consumption, and the data used for estimating the type and the posture of the wild animal is acquired. In the sensor node in the proposed system, the microcontroller first receives the "approach" or "separation" signal from a doppler sensor, and when the type of received signal is "approach", it activates the small computer by controlling a relay circuit. Next, the activated small computer estimates the type and posture of the approaching wildlife by applying the image analysis process described in the next section to the temperature images that are obtained from the connected thermal camera.

D. Analysis method of temperature image in sensor node

In this research, LTE-M which is a type of LPWA is used as the communication method for sending data from sensor nodes to the analysis server, hence it is difficult to send large amounts of data such as images in real-time. Therefore, the proposed system adopts a system structure of edge computing configuration where the temperature images obtained from a thermal camera are analyzed in the sensor node, and only the estimated results of the type and the posture of the wild animal are sent to the analysis server. The data to be sent to the analysis server is summarized in Tab. I. As shown in this table, the data consists of the sensor ID to identify the location where the sensor node is installed, the estimated type/posture/the average number of wildlife, and the time when the wildlife is detected. In the following parts of this section, Section III-D1

TABLE I
FORMAT OF DATA SENT FROM THE SENSOR NODE TO THE ANALYSIS SERVER.

Data name	Type	Example
Sensor ID	char	01
Estimated class	char	human_front
Average number of animals	float	2.2
Acquisition time（UNIX）	char	1605364660851.75

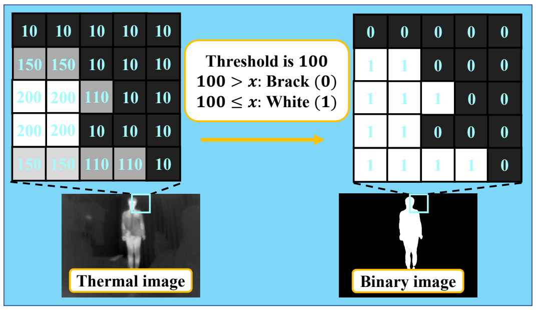

Fig. 3. Binarization method to convert thermal image to binary image (threshold value is 100).

describes the detailed process of extracting the contours of the wildlife from the temperature image as a pre-processing for machine learning, and Section III-D2 describes the detailed process of estimating the type and posture of the wildlife by the machine learning.

1) Binarization process for thermal images: As a pre-processing step for machine learning, a binarization is applied to the temperature images captured using the thermal camera to emphasize the contours of the wild animals in order to reduce noises on the temperature image and to focus on the part of the wildlife on the image for the analysis. The procedure for generating a binary image from the temperature image is shown in Fig. 3. As shown in this figure, a threshold value for the binarization is predetermined. If the grayscale value corresponding with the temperature in the pixel is smaller than the threshold, the value of the pixel is set to 0. If the value is greater than the threshold value, the value of the pixel is set to 1. In the binary image in Fig. 3, a pixel with a value of 0 is black, and a pixel with a value of 1 is white. In the proposed system, the different thresholds are selected among the different environments (i.e., 90 for indoors and 170 for outdoors) because the brightness that affects the grayscale value varies depending on the environment.

2) Estimation process of the type and posture of wildlife using machine learning: The small computer is a component of the sensor node that estimates the type and posture of the wildlife in the temperature image by applying the machine learning technology to the binary image generated by the process described in the previous section. In our proposed system, we use YOLO which is one of the object detection models using deep learning as a machine learning technology [8]. By inputting a binary image to the pre-built learning model of YOLO, the location and the existing probability of each type of object in the image are estimated. Since we have not obtained temperature images of actual wildlife enough to construct the learning model yet, the analysis target of the proposed system is a human that is a kind of organism as shown in Fig. 4. As shown in this figure, the input image is firstly divided into 5×5 cells. After that, the proposed method predicts the bounding rectangles where the object may exist and the map where the object may exist. Finally, it combines the bounding rectangles with the map and outputs the estimation result.

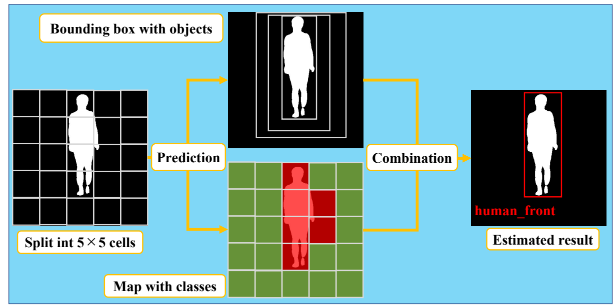

Fig. 4. Method for estimating animals by machine learning.

After waking up, the small computer starts the process of estimating the type and posture of wildlife every 10 seconds. First, all the binary images captured and generated during 10 seconds are input to the machine learning model to obtain the result in each image. And then, a majority vote is taken on all the estimation results based on the images, and the type, posture, and the average number of the most numerous wild animals are calculated. Finally, the results are sent to the analysis server.

IV. PRELIMINARY EXPERIMENTS TO DERIVE APPROPRIATE SETTINGS FOR MACHINE LEARNING

In this section, we describe the types of machine learning technology (YOLO) used in this study, and preliminary experiments to study the appropriate combination of libraries for implementing machine learning. In this experiment, we assume that the target organism is one type of human being and build a machine learning model to estimate three different postures to the camera: “facing front/facing right/facing left”.

There are two types of YOLO: version 3 (YOLOv3) which runs stably on the Raspberry Pi 4B, and YOLOv3-Tiny a lighter version. Each type is used together with TensorFlow which is a library for deep learning provided by Google or Keras which is an open-source library for building neural networks. In addition, TensorFlow version 2 (hereinafter, referred to as TF2) is used because YOLOv3 and YOLOv3-Tiny may not work with TensorFlow version 1.

A. Impact of the type of machine learning library

In order to clarify which library (TF2 or Keras) of the machine learning is appropriate for our proposed system, we evaluate the time taken to estimate and the estimation accuracy

TABLE II
YOLOv3 + TF2 vs. YOLOv3 + KERAS

Pair	Detection time (sec)	Accuracy rate
YOLOv3 + TF2	31	1.0
YOLOv3 + Keras	43	1.0

TABLE III
YOLOv3 + TF2 vs. YOLOv3-TINY + TF2

Method name	Detection time (sec)	Accuracy rate
YOLOv3 + TF2	31	1.0
YOLOv3-Tiny + TF2	0.7	1.0

for the combination of YOLOv3 and TF2, and the combination of YOLOv3 and Keras. In this evaluation, 32 images with the correct label of human_front (human is facing front) are used as training data to build the learning model. For the constructed learning model, 10 images that are different from the training data are input to the learning model to estimate the posture of the target, and the average time required for estimation and the percentage of accuracy is estimated.

The experimental results are shown in Tab. II. From this table, we can see that the accuracy rate is 1.0 for all combinations but the time taken to estimate is 31 seconds for the combination of YOLOv3 and TF2 which is faster than the combination of YOLOv3 and Keras. Based on the result, TF2 is used as the machine learning library in the subsequent experiments.

B. Impact of the version of YOLO

In order to clarify which version of YOLO is appropriate for the proposed method, we evaluate the performance in case that each version of YOLO (i.e., YOLOv3 or YOLOv3-Tiny) is used. The procedure for constructing and evaluating the learning model is the same as that in Section IV-A.

The experimental results are shown in Tab. III. From this table, we can see that the correct answer rate is 1.0 for both versions of YOLO, but the required time for YOLOv3-Tiny is about 44 times faster than that for YOLOv3. In general, the YOLOv3-Tiny is known to have lower detection accuracy than YOLOv3, but there is no degradation in estimation accuracy when using YOLOv3-Tiny because of the binarization preprocessing can emphasize the contours of the target. In addition, it is necessary to consider the improvement of estimation speed by using YOLOv3-Tiny rather than the estimation accuracy by using YOLOv3 because the proposed system needs to notify the administrator of the appearance of harmful birds and animals in real-time. Therefore, the YOLOv3-Tiny is adopted as the version of YOLO in the following evaluation in this study.

V. DEMONSTRATION EXPERIMENT TO EVALUATE THE EFFECTIVENESS OF THE PROPOSED SYSTEM

In order to clarify the effectiveness of the proposed system, we evaluate the power consumption of the sensor nodes and the performance of detecting the type and posture of wildlife using machine learning.

TABLE IV
POWER CONSUMPTION OF EACH DEVICE

Device name	Electric current	Power consumption
Arduino Nano Every + NJR4265 J1 (Always-on startup)	0.104 A	0.52 W
Raspberry Pi 4B (Reading and writing images)	1.13 A	5.65 W
Raspberry Pi 4B (During object estimation)	1.40 A	7 W

A. Evaluation of power consumption of sensor nodes

In this experiment, we measure the power constantly consumed by the microcontroller with the doppler sensor, as well as the power consumed by the small computer when the process of estimating the type and posture of wild animals. Based on the measurement result of the power consumption, the maximum time that the proposed system can operate continuously when using a battery with a capacity of 12 Ah is estimated.

The experimental results are shown in Tab. IV. As shown in this table, the current consumed by the microcontroller with a doppler sensor is 0.104 A. Based on the evaluation results of the current consumption, the proposed system can operate for only 60 hours even if the small computer is periodically activated three times per hour when using a battery with a capacity of 12 Ah. In the previous study, the wireless beacon device is used to detect the approaching of the moving object [5] and the power consumption of the device is $10 \sim 20$ mA which is much smaller than the combination of microcontroller and doppler sensor used in the proposed system. This is mainly due to the fact that the current consumption of the doppler sensor is 60 to 70 mA.

B. Evaluation of the performance of machine learning for object estimation

In this section, we evaluate the performance of the machine learning model described in Section IV. At present, it is difficult to install the prototype system in an actual field where wild animals live (e.g., mountainous areas). Therefore, we conduct an experimental evaluation that the detection target is a human on the campus of Ritsumeikan University, Japan.

The experimental results are shown in Tabs. V and VI. From these tables, it can be seen that the proposed system can estimate that the posture of the human with an accuracy of about 94% when the distance between the thermal camera and the subject is 3 m. However, when the distance between the thermal camera and the subject is 5 m, the accuracy decreases to about 45%. This is because, with the increase in the distance, it is more difficult to obtain the correct temperature of the surface of the subject. Therefore, in order to accurately estimate the type and posture of wildlife by the proposed system, it is necessary to build the learning model for each specific distance range.

TABLE V
DISTANCE IS 3 M

Label of correct \ Label of estimation	human_front	human_right	human_left
human_front	161	-	-
human_right	-	138	2
human_left	-	7	163

TABLE VI
DISTANCE IS 5 M

Label of correct \ Label of estimation	human_front	human_right	human_left
human_front	132	1	22
human_right	-	70	2
human_left	-	56	52

VI. SUNSHINE HOURS REQUIRED FOR PERMANENT OPERATION OF THE NEW TYPE OF SENSOR NODES

Based on the measurement results in Section 5, we are considering a design of a new type of sensor node considering the microcontroller and the small computer. In the sensor node, the microcontroller detects the existence of the wildlife using the wireless beacon device to reduce the power consumption and sends a signal for activation once when detecting the wildlife. In addition, the small computer is equipped with the 3D LiDAR for observing the detailed shape of the target to identify the type and posture of the wildlife. In the proposed system, the microcontroller is an Adafruit Feather nRF52840 express, the 3D LiDAR is a Mid-70, and the small computer is a Jetson Nano.

When detecting the moving object in the vicinity, the microcontroller activates the small computer and the 3D LiDAR by transmitting a signal to the relay circuit. After that, the small computer wakes up from the suspend mode and acquires 3D point cloud data of the target object for 60 seconds from the activated 3D LiDAR.

In this experiment, we consider the sunshine hours required for the permanent operation of the sensor node consisting of the microcontroller and the small computer when using a power generation system consisting of a battery with a capacity of 50 Ah and a solar panel with a maximum output of 100 W. In the sensor node of this experiment, the microcontroller sends a signal for activation once an hour to the small computer and the relay circuit to which the 3D LiDAR is connected. After that, the small computer that has recovered from the suspend mode acquires 3D point cloud information of the target object from the activated 3D LiDAR. Here, it is assumed that the microcontroller detects the moving object and activates the small computer once per hour.

Here, the sunshine duration provided by the Japanese Meteorological Agency during the experiment in Otsu City, Shiga Prefecture, Japan, is shown in Fig. 5. As shown in this figure, if the total amount of sunlight in a week is 1127 minutes (about 18.9 hours), the system can operate semi-permanently because the amount of electricity generated by the power generation system exceeds the power consumption of the sensor nodes.

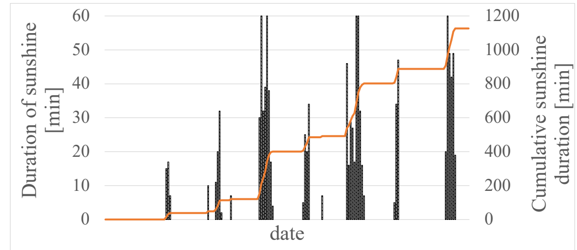

Fig. 5. Sunshine hours in Otsu City, Shiga Prefecture, Japan from July 8 to 15, 2021

VII. CONCLUSION

In this study, we have proposed a new sensor network system that detects the presence of wild animals by analyzing images taken by the thermal camera. In addition, we have achieved power saving of the entire system by activating from the sensor with low power consumption to the sensor with high power consumption in stages. Furthermore, by analyzing the captured images taken by the thermal camera using a machine learning technology, we have shown that the system can distinguish not only the type and the number but also the posture of the animals. In the future, we will propose a new sensor network system that detects the presence of wild animals by analyzing point cloud data measured by the 3D LiDAR so as to accurately observe the type and posture of the wildlife. In addition, we will collect wild animals' data from sensor nodes installed in the field and analyze the data.

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