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Intelligent beehive monitoring system based on internet of things and colony state analysis

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ABSTRACT

Bees play a crucial role in terrestrial ecosystems. However, beekeepers are unable to monitor the state of beehives (bees and environment) all the time, which often results in bees escaping or even dying. Currently, some researchers provided the scheme of intelligent beehive monitoring system equipped with the Internet of Things (IoT), There remain two challenges: accurately monitor the environmental status around the hive and accurately track and monitor bees in real time. With the development of the IoT and computer vision algorithms, we hope to provide an automated and efficient system to meet the above challenges. In this paper, we proposed a hive monitoring system, and build a visualization module in the cloud to monitor the activity of bee colonies and the environmental dynamic changes. (1) We proposed a multi-bee tracking algorithm to solve the problem of monitoring bees at the door of the hive; (2) we constructed a dataset containing various complex scenes, named BEE22, for training and testing the performance of our algorithm; (3) we designed a bee counting rule, based on results of multi-bee tracking algorithm, to reasonably count the bees entering or leaving the beehive; (4) we have deployed multiple sensors around(center, margin, door, and environment) the hive to accurately reflect the changes in the environment around the hive. Experimental results demonstrate the effectiveness and excellence of our system. In particular, the tracking performance of the multi-bee tracking algorithm reaches 83.5 % $\pm$ 0.7 % Multiple Object Tracking Accuracy (MOTA) and 77.3 %$\pm$0.2 % Multiple Object Tracking Precision (MOTP), speeds up to 16 frames per second, compared with other algorithms, MOTA and Identity F1 Score (IDF1) are improved by 5.4 % and 8.2 % respectively. Moreover, our counting algorithm also achieved excellent results, with root mean square error (RMSE) of 1.3 $\pm$ 0.1, 0.2 $\pm$ 0.0, and 1.6 $\pm$ 0.1 in counting the number of bees current, entry, and out scene in an episode, respectively. After that, the system will be deployed and monitored for a long time in the actual scenario, it was found that the activity of bees decreased significantly under heavy rainfall conditions. Additionally, the activity of the bee colony will also increase accordingly, when the amplitude is 500 dB to 2000 dB, the temperature of the center of the beehive is 25 °C to 37 °C, and the humidity is 48 % to 67 %. In summary, our system can provide valuable information for bee farmers to make control decisions on hives.

1. Introduction

Bees play a crucial role in terrestrial ecosystems, especially for those flowering plants, whose normal flowering and fruiting is usually based on bee pollination [1]. The European Union Conference once pointed out that nearly 80 % of the world's food crops are pollinated by bees [2]. With the global food challenges brought about by the continuous population growth, the transformation and upgrading of the bee farming

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industry, which is the "guarantee army" of food production, is urgent [3].

Although constant improvement has been made, human beings still face many challenges today, such as bee separation [4] and the collapse of bee colony barriers [5]. The reason is that so far, most beekeepers still adopt traditional manual management methods, including regularly observing the activity of bees in the area near the door of the beehive and opening the beehive to obtain information inside the beehive [6]. Beekeepers will judge the status of the bee colony based on this information and their previous beekeeping experience and then take corresponding control strategies. It is impossible to know about the status of the bee colony in a timely and accurate manner only by this manual management method, which leads to a lag in the management of the bee colony by beekeepers, resulting in many losses. In addition, there are still many limitations in traditional management methods. On the one hand, the colony state is generally normal, meaning that the daily monitoring of beekeepers is not only time-consuming and labor-intensive but also inefficient. On the other hand, frequent opening of beehives will cause certain disturbances to the life of bees.

The automated monitoring of bee activity provides new ideas for beehive management. In this regard, researchers have done much exploration work [7-11]. Early popular monitoring methods include photoelectric sensors [12], capacitive sensors [13], and radio frequency identification [14], but these methods can only be used to count the number of bees passing through the door of the hive, which is not enough to measure the overall situation of the bee colony. This is because there are different species of bees in the colony, such as guard bees, which stay nearby or hover to guard the nest [15], while forager bees fly away from the hive to forage for food at a distance [16]. Therefore, to effectively assist beekeepers in making a reasonable assessment of bee colony status and potential risks, automated monitoring methods are required to provide more dimensional information, including the number of bees near the door of the beehive and the number of bees in attendance, etc.

The development of image sensors and computer vision technology in the past two decades has provided a potential solution to the above tasks. Specifically, these tasks can be viewed as object detection and multi-object tracking problems in computer vision. The object detection task requires the algorithm to locate and identify all the objects of interest in a given picture [17], while the multi-object tracking task further requires the algorithm to match the same object in any two adjacent frames of the image sequence while simultaneously processing objects coming and leaving the scene [18]. In recent years, many computer vision-based methods have been applied to the task of monitoring bee activity outside the beehive, like support vector machines [19], Gaussian mixture models [20], Canny contour recognition [21] and other methods, all are used to detect bees in images, to acquire statistics on the number of bees in the scene. For the problem of tracking multiple bees in an image sequence, several methods such as Bayesian tracker [22], Kalman filter [23], and optical flow method have emerged [24] to count the number of bees entering and leaving the hive door according to the observation of the designed entry and exit division area. However, the division of the entry and exit areas by the above methods is based on subjective experience, which will cause a significant counting error, especially when the bees are in the honey collection period [25]. Then, when the statistics of the number of bees entering and leaving are in units of days, the data obtained by the current method will be far from the actual situation, resulting in a wrong conclusion. In addition, the practical application scenarios also pose many challenges to these algorithms, including (1) the appearance of bees is highly similar, and it is challenging to extract differentiated features; (2) the bees will undergo non-rigid deformation during movement, thus changing the appearance features; (3) the bees in the scene will produce severe mutual occlusion in dense situations, resulting in missed detection; (4) the movement patterns of bees are complex and changeable and difficult to predict. In light of the above challenges, a series of methods currently used can only be applied for monitoring tasks when there are only a few bees and a relatively small degree of movement due to the limitations of insufficient representation ability and poor robustness. They cannot be applied in long-term and accurate monitoring of bee activities in complex and changeable scenarios.

Benefiting from its powerful representation ability and generalization performance, deep learning technology has been brilliant in computer vision and other fields in recent years. Some deep learning-based computer vision methods have been successfully applied and implemented in various industries [26,27]. However, to the best of our knowledge, there are few studies that combine deep learning technology with monitoring of bee activity outside the hive. For the bee detection task, neither the Faster-RCNN algorithm [28] nor the YOLOv3-tiny algorithm [25] currently used by researchers can achieve a balance between accuracy and speed. However, the research on deep learning to solve the multi-bee tracking task is still blank. Therefore, according to the existing challenges of bee monitoring tasks outside the beehive and the shortcomings of current application methods, based on deep learning, this paper proposes a tracking-by-detection (TBD) and tracking framework and constructs a large-scale sequence dataset of bee activity images for deep learning. The training and testing of the model realize long-term, accurate all-weather automatic real-time monitoring of the number of bees entering and leaving the beehive door and the activities of nearby bee colonies.

In addition to monitoring bee colony activity, the environmental status inside and outside the beehive [7] is also an important indicator for assessing bee colony status. Studies have shown [29] that honeybees usually require a suitable range of weather conditions for temperature and humidity to participate in foraging activities. However, the human body cannot accurately perceive environmental states such as temperature and humidity. If beekeepers formulate control strategies based on this information with significant errors, it will inevitably bring unpredictable adverse effects to the bee colony. Therefore, using precise equipment to automatically monitor the environmental conditions around the beehive is also an urgent problem to solve in the field of bee farming.

In the past ten years, scholars have tried different sensing technologies to measure the status of bee colonies, including temperature [30], humidity [31], sound [32], weight [33], and chemical [34] sensing. However, many states of a bee colony, such as foraging, bee splitting, and other behaviors, are often influenced by multiple environmental factors [35]. Therefore, using only a single sensor is not sufficient. Some current work has considered this issue and combined the above sensing techniques in different ways, trying to reveal the quantitative relationship between the environment and some specific swarming phenomena, such as colony barrier collapse [36,37]. It is worth noting that the environmental states of different areas around the beehive are pretty different. For example, the temperature outside the beehive changes with sunrise and sunset, while the temperature in the center is relatively constant [38]. Therefore, it is challenging to reflect the actual environmental state by relying only on a single location's sensor data. In this paper, we consider installing multiple sets of multi-type sensors at different positions of the beehive to reasonably describe the environmental state around the beehive.

In summary, Our study offers five notable contributions: (1) a multi-bee tracking algorithm, which combines motion and appearance features to effectively solve the mutual occlusion and ID switching between bees, (2) an automated and ecient system to continuously monitor the status of bee colonies in beehives, which can help beekeepers achieve better hive management, (3) a counting algorithm that can accurately count bees, (4) after long-term monitoring combined with comprehensive environmental factor data, quantified the relationship between bee activity and the surrounding environment, (5) construct a bee tracking dataset, and a dataset of an omnidirectional beehive environment, including temperature, humidity and sound, which is similar to the current related datasets.

2. Materials and methods

2.1. System framework

In this paper, a set of beehive automatic monitoring systems is proposed to realize long term automatic monitoring of bee colony status and surrounding environment status in the beehive. The system framework is shown in Fig. 1 On the right side of the figure is the beehive. The black rectangle on the beehive represents the doorway for bees to enter and exit. In the beehive, we have deployed temperature and humidity sensors at the center, margin, and door of the beehive. The sound sensor is installed in the center of the hive, and the webcam is deployed at the upper left of the beehive door. A group of temperature and humidity sensors is installed on the circular buckle outside the beehive. We divide all the sensors into two modules. One is the bee activity monitoring module at the door of the beehive, which is mainly composed of webcams; The other is the beehive environment sensor module, which is mainly composed of temperature, humidity, and sound sensors. Additionally, we transmit the collected information about the state of the hive and the honeycomb environment to the cloud computing service for algorithm processing, storage, and visualization.

2.1.1. Automatic monitoring equipment

In this study, we designed and built a set of sensing equipment on a conventional beehive for production, relying on the Fujian Bee Biology Science Observation and Experiment Station of the Ministry of Agriculture. As shown in Fig. 2, the installed equipment includes vision, temperature, humidity, and sound sensors distributed inside and outside the hive to automatically monitor the status of the bee colony and the environment inside and outside the hive.

The beehive selected in this experiment is shown in Fig. 2(a), with a size of 51 × 41 × 26 cm. The beehive has an opening at the top and is equipped with a beehive cover for the daily management of beekeepers. It should be noted that the light source at night will disturb routine work and the rest of the bee, so no additional light source is added during the experiment.

2.1.1.1. Visual sensing equipment. In order to meet the needs for long-term monitoring of bee colony status, this paper adopts a network camera with an automatic exposure adjustment function (Hikvision EZVIZ C3C full-color version as shown in Fig. 2(a)) to collect images data with stable quality under different lighting conditions. The webcam is located at the upper left corner of the door of the hive, and has a resolution of 2560 × 1440, a frame rate of 25 frames per second, a focal length of 2.4 mm, and a video encoding method of H.264. During the installation process, we first used rivets to embed a 20 × 10 × 3 cm wooden board at the upper left edge of the bee entrance and exit side of the beehive and separated from the beehive cover, and then fixed the camera on this board. To obtain an image with sufficient clarity and to allow the scene from the camera's perspective to sufficiently cover the active area of most bees near the door of the beehive, we repeatedly adjusted the position and angle of the camera and finally determined the position of the camera on the beehive's door. The left side of the entrance and exit is 51 cm, the front side is 15 cm, and the top is 26 cm. At the same time, the camera is aimed at the bee's entrance and exit.

Additionally, to reduce the interference of the image background to the visual algorithm, we covered the entire box surface on the bee entrance and exit with the off-white background paper, leaving only the beehive entrance area. It is worth mentioning that beekeeping experts recommend using off-white background paper because some other colors may be offensive to bees and interfere with their routine living habits.

2.1.1.2. Environment sensing equipment. The activity of a bee colony is affected by the state of the environment [39], For example, when the temperature and humidity are suitable, bees will actively participate in foraging activities. According to the comparative analysis, this paper will use temperature, humidity, and sound sensors to monitor the environmental status of the beehive. In addition, bees are more sensitive to the perception of environmental conditions. Indeed, the bee colony will autonomously regulate the temperature in the center of the hive, which is constant at around 35 °C [40]. Therefore, to accurately analyze the impact of the environment on the state of the bee colony, it is necessary to use sensor devices with sufficient accuracy.

To accurately measure the temperature and humidity around the beehive and minimize the impact of sensor equipment on the activity of the bee colony, this paper uses a probe sensor model YC-A, which combines temperature and humidity monitoring functions to measure, the sensor has a length of approximately 50 cm and can detect the center of the beehive. The accuracies are 0.1 °C and 1.5 % respectively, and the dimensions are 3.3 × 0.3 cm, as shown in Fig. 2(b). Additionally, the sensor has a measurement range of −40 to 125 °C and 0 to 100 % RH for temperature and humidity, respectively, with a data acquisition frequency of 1 time per second, and is equipped with a waterproof and moisture-proof protective case. Since the interior of the beehive is almost a closed space, and there are a large number of bees moving inside the beehive, there may be large differences in temperature and humidity in different areas inside and outside the beehive. The measurement data of a single location is not enough to reflect the real environment around the beehive. Therefore, we deployed four temperature and humidity sensors at different locations inside and outside the beehive. One of the sensors is fixed on the edge of the beehive through a circular buckle to collect the temperature and humidity of the external environment; the other three are respectively installed at the door of the beehive, the center of the beehive, and the margin of the beehive. The specific locations of these four sets of temperature and humidity sensors as shown in Fig. 2(b).

In addition to temperature and humidity, sound is also an important

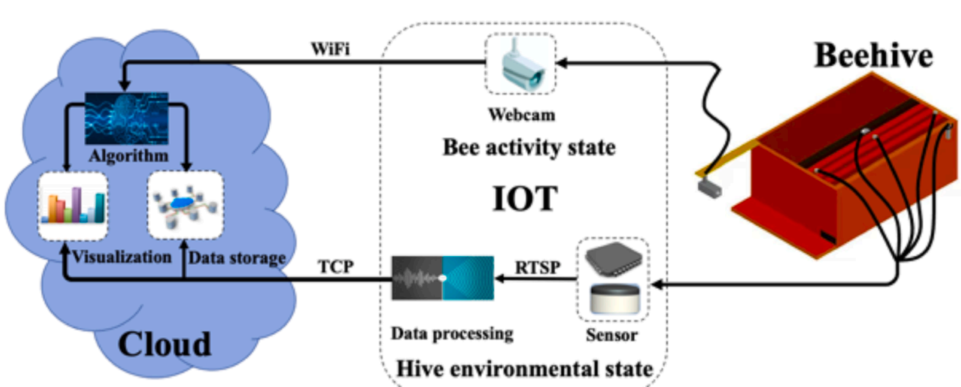


Fig. 1. Beehive monitoring system.

(a) Vision sensor (b) Environmental sensor

Fig. 2. Deployment of sensors in the real environment.

indicator for assessing the environmental state of a bee colony. Since the sound frequency range that bees can emit is around 300 Hz [41], we used a DS-923AT sound sensor produced by Shenzhen Fiberhome Audio, whose response frequency range is 20 to 20,000 Hz. Considering that our primary concern is the state of the bee colony, and at the same time to avoid affecting the colony, we fixed the sound sensor in the center of the back of the comb through push pins. The specific location of the sound sensor as shown in Fig. 2(b).

2.1.2. Data collection and processing

After the visual sensing device is activated, the area near the door of the beehive will be used as the monitoring scene, and the video will be automatically shot at a frame rate of 25 frames per second for 24 h without interruption to achieve the long-term, all-weather and real-time recording of bee colony activities. The captured video needs to be further processed by detection and tracking algorithms. This paper uses a cloud computing service as the model inference platform, considering the high requirements of the algorithm on computing performance. Before that, we need to transfer the video from the local to the cloud computing services. We use 300 megabytes of bandwidth on both the local and cloud servers, and the transmission speed of 4 million pixel video images can reach 25 frames per second. To ensure transmission stability, we use EZOPEN, the private protocol of the EZVIZ camera, as the network transmission protocol. Due to the large area covered by the original shooting scene, we were only interested in the main activity area of the bees near the hive door outside the hive. Therefore, after the cloud server obtains the image stream from the video, the image is first preprocessed. That is, the region of interest is obtained by image cropping to reduce the interference of irrelevant backgrounds and improve the processing speed of the algorithm. Fig. 3 shows the scene comparison of the image before and after the cropping. The final reserved area is a 15.7 $\times$ 12.56 cm rectangular scene, and the resolution is reduced from 2560 $\times$ 1440 of the original image to 950 $\times$ 600. The algorithm then detects, tracks, and counts the bees in the cropped image.

For monitoring the bee colony environment, the temperature and humidity sensors used in this paper will collect data at a frequency of 1 time per second and automatically forward the collected data in real-time through its built-in WIFI module. Similarly, environmental data is also transmitted to our cloud computing server, and the network transmission protocol used is Transmission Control Protocol (TCP) to ensure the stability of data transmission. Since the temperature and humidity data are text data and the amount of data transmitted each time is small, real-time transmission performance can be achieved. However, the sound sensor acquisition is an analog signal containing a large amount of data that cannot be transmitted in real-time by TCP. Therefore, this paper first installs a jetson TX2 embedded board locally to transmit data in real-time through Real-Time Stream Protocol (RTSP), then performs Fourier transform on the collected sound analog signal to amplitude data, and then resample at one time/*sec*. The preprocessed sound data can be transmitted in real-time through MySQL.

At the same time, we get the local weather conditions every hour by calling the weather API (URL=http://wthrcdn.etouch.cn/weather_mini?citykey=101230101), and then transfer it to the database through MySQL.

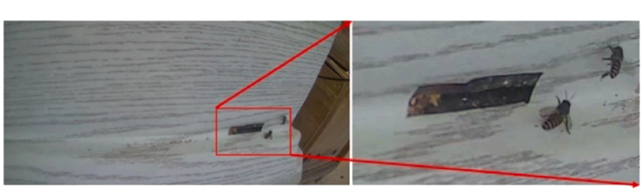


Fig. 3. The clipping of the detection area.

2.1.3. Data storage and backup

To use a large amount of beehive monitoring data for further analysis, we need to take some means of integrated management, and the database is a suitable one. Based on the MySQL database, this paper builds a set of beehive monitoring databases on the cloud computing services to realize the functions of storage, import, export, and update of visual, temperature, humidity, and sound sensor data. Tables S1, S2, S3, and S4 show the database field tables of temperature, humidity, sound, activity, and weather, respectively. Then the data is backed up on the cloud storage server.

2.1.4. Data visualization

To allow beekeepers to know about the overall situation of the bee colony in a timely, accurate, and intuitive way, this paper combines MySQL database and data visualization software to design and develop a visualization system for monitoring bee colony status and beehive environment. In Fig S4 and Fig S5, we show the environment and activity monitoring.

2.2. Algorithm description

2.2.1. Multi-Bee tracking algorithm

The bee activity monitoring algorithm at the door of the beehive used in this paper is shown in Fig. 4. and YOLOv5 [42] is used as the detector. Compared with Faster-RCNN [43], YOLOv5 is a single-stage detection algorithm, which does not need to generate candidate regions during detection, and can directly regress the object category and boundary, significantly improving the detection speed. Then, DeepSORT [44] is used as a multi-object tracker, which can reduce id switch and improve tracking accuracy compared with traditional tracking algorithms.

The network framework of YOLOv5 is mainly composed of input,

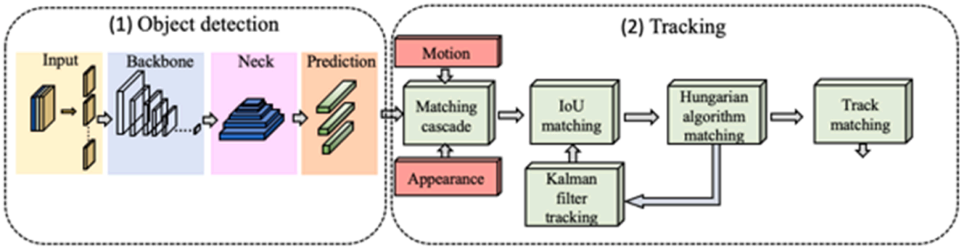


Fig. 4. The framework of the multi-bee tracking algorithm.

backBone, neck, and prediction. In the Input stage, to augment the data, the image is preprocessed. Then, in the backBone stage, the image is cropped by the focus structure, and the data is divided into four parts, each equivalent to 2 times downsampling, and a convolution operation is performed after splicing on the vertical channel. The bottleneckCSP and spatial pyramid pooling (SPP) are used in the neck network. The former reduces the amount of calculation and improves the inference speed, while the latter realizes the feature extraction of different scales for the same feature map, which is helpful for the improvement of detection accuracy. In the final prediction stage, the head model is mainly used to predict the final result, the anchor frame is marked in the grid according to the feature, and the probability of the object class and the final position of the frame are calculated through the loss, and the generalized intersection over union (GIOU) loss is used as the loss function of the bounding box, so the border has a speedy and good convergence effect.

Object occlusion is a big challenge in tracking algorithms in complex motion situations. In order to solve this problem, the DeepSORT algorithm adds appearance information to the cascade matching, improves the tracking effect of object occlusion, and reduces the situation of object jump (ID Switch). The workflow of the algorithm is as follows: first, create the corresponding Tracks from the results detected in the first frame, and at the same time, initialize the motion variables of the kalman filter, and predict the corresponding frame through the kalman filter. Then, intersection over union (IoU) matching is performed in turn between the frame detected by the object frame and the frame predicted by tracks in the previous frame, and then the cost matrix is calculated based on the result of the IoU matching, and all the cost matrices are used as the input of the hungarian algorithm to obtain a linear matching. As a result, the boxes corresponding to its confirmed tracks and unconfirmed tracks are predicted by kalman filtering. Finally, there are three possible results after cascading matching. The first is tracking matching. Such tracks update their corresponding tracks variables through kalman filtering. The second and third types are mismatches between detections and tracks. At this time, the previously unconfirmed tracks and the mismatched tracks are matched with the unmatched detections in turn for IoU matching, and then the cost matrix is calculated based on the result of the IoU matching.

2.2.2. Bee counting algorithm

To quantify the state of the bee colony, we consider monitoring the bees near the door of the beehive based on the depth vision algorithm and counting the number of bees entering or exiting the hive as well as the number of bees outside.

To this end, we designed a rule for judging bees entering and exiting the nest. The red box indicates the boundary of the bee's entry and out of the nest. There are four bees in the figure, namely, No 1, No 2, No 3, and No 4. The bees in the gray box indicate the position of bees in the current frame, and the bees in the white box indicate the position of bees in the previous frame. In the upper left corner of the figure, the number of bees in and out and the number of bees in the current scene is calculated. as shown in Fig. 5. Use the tracking results of the algorithm to obtain the relationship between the position of the bee at the current moment and the previous moment and the bounding box. The basis for bees entering the nest is that the center of the bee is outside the bounding box at the previous moment, and the current moment is within the bounding box; the rule for bees to leave the nest is that the center of the bee is outside the bounding box at the previous moment, and disappears from the scene at the current moment. Fig. 5, at the moment, the No 1 bee will be judged to be in the nest, the No 4 bee will be out of the nest, and the No 2 and No 3 bees are not in the state of entering or leaving the nest, so the number of bees entering and leaving the nest is 1.

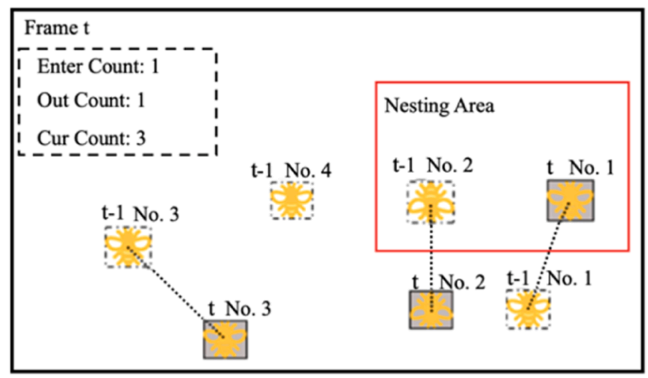


Fig. 5. the block diagram of the bee counting algorithm.

Additionally, for the statistics of the number of areas outside the beehive, also known as the number of statistics in the scene, it is only necessary to count the number of bees tracked at the current moment. Therefore, in Fig. 5, the number of bees in the outer area of the hive is 3.

3. Results and discussion

3.1. Experimental conditions

The development and deployment of the sensor start in the summer and autumn of 2021 at the Bee Observation Base of the Ministry of Agriculture of Fujian Province, with data collection from March 1st, 2022, to May 31st, 2022. In the data analysis in Section 3.5 only shows the analysis results from March 1rd, 2022 to March 29th, and the data from other months are used as supporting materials. The beehives are the existing beehives in the bee observation base; and our beehive has three nests, and the bees are Chinese honeybees. We collect data monitored 24 h a day, and due to the summer and autumn seasons, the ambient temperature is around 18 °C to 30 °C.

3.2. Implementation details

The detection and tracking models are trained on cloud computing services with a 3090 graphics card with 12 G of video memory. The detection tracking and counting algorithms are implemented using python based on the PyTorch framework. At the beginning of the training phase, the training image of the YOLOv5 model is resized to 640 × 640 pixels. Subsequently, images are used to increase the amount of training data and the robustness of the model. Enhancements include random changes in exposure, saturation, hue, and rotation. In order to ensure the reliability of the experiment, 10 groups of models are trained, the seed of each group of models is from 50 to 59, and calculate the standard deviation based on these 10 sets of results, the batch size is set to 32, and the initial learning rate is 0.001. To monitor the progress of the training process, the average loss and mean precision (mAP) were tested every 50 times. Each set of training was performed for 600 iterations. After 600 iterations, the average loss of the model converged to below 0.17. Maps are all over 90 %, indicating that the trained model is not overfitting. As a tracker, DeepSORT also trains ten groups of models, with seeds ranging from 50 to 59, with an initial learning rate of 0.001, and each group is trained for 600 iterations.

3.3. Dataset

In this paper, we constructed a BEE22 multi bee tracking dataset. In order to fully reflect the various activities of bees, we removed the blurry and motionless videos, and finally collected 16 videos with significant differences in bee movements. For annotations, we use DarkLabel 2.1, a free and public MOT labeling software to annotate the dataset. (details can be found at: https://github.com/darkpgmr/DarkLabel). Before starting the annotation, we set the record format to (frame, id, x, y, w, h), this format is consistent with the MOT17 [55] dataset to ensure the integrity of our tracking dataset. Afterwards, when annotating, for some bees with more than two-thirds of their bodies outside the image and weak bee features, we do not annotate them to ensure accurate detection of bees by the model, as shown in Fig. 6. Based on this, we obtained 16 sets of image sequences with a frame rate of 25 and a resolution of 950 × 590, consisting of 627 bees and labeled with 31,348 tags, as shown in Table 1. The complete dataset is available at https://drive.google.com/file/d/1jSlhbEItF9nOVlnNchSS3KE8HxMFYQYl/view?usp=drive_link.

In the real environment, the number of bees entering and leaving the hive varies greatly at different times in a day. In order to make the model proposed in this paper more robust, the BEE22 data set contains different periods and different numbers of bees. The situation is divided into three levels: easy, medium, and difficult. The Fig. 7 shows the frequency of the number of bees at different levels: the number of bees in the simple scene is no more than ten, and it is relatively stable (Fig. 7a); the number of bees in the medium scene varies from 8 to 20 (Fig. 7b); the number of bees in the difficult scene is larger, from 9 to 29, and the change is obvious (Fig. 7c), mainly due to the fast movement of bees in difficult scenes, resulting in large changes in the number of bees. At the same time, we select three images from all image sequences as test data, namely: BEE22–12 (easy), BEE22–16 (medium), and BEE22–13 (difficult).

3.4. Comparison of method performance

3.4.1. Evaluation of multi-bee algorithm

For the performance evaluation, we use the widely accepted MOT metrics including Multiple Object Tracking Accuracy (MOTA), IDF1 score (IDF1), Mostly Track object (MT), Mostly Lost object (ML), False Positives (FP), False Negatives (FN), ID switches (IDS), etc. Among these metrics, MOTA and IDF1 are the most important ones. MOTA represents the tracking accuracy considering false positives, missed object, and identity conversion. IDF1 represents the comprehensive accuracy of identity accuracy and recall rate. The larger their values, the better the performance of the model.

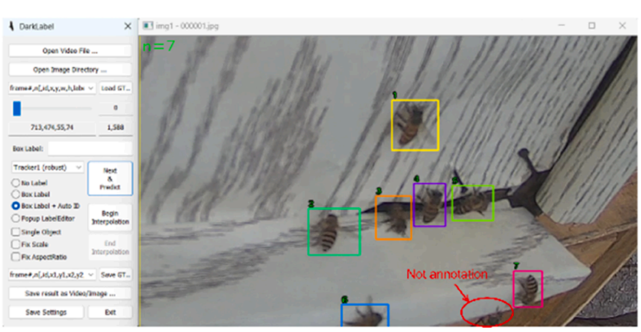


Fig. 6. DarkLabel annotation data.

Table 1
Information on the BEE22 dataset. The sequence name, pixel, frame rate, time, number of bees, and number of labels of the BEE22 dataset are shown. There are 16 image sequences in total. In the same image sequence, each bee in each frame is a label, and the number of labels in each image sequence is finally counted.

Image Sequence	Pixel	Frame Rate	Time (frame)	Number of Bees	Number of Labels
BEE22–01	950 × 590	25	75	14	501
BEE22–02	950 × 590	25	75	11	416
BEE22–03	950 × 590	25	75	10	415
BEE22–04	950 × 590	25	75	14	378
BEE22–05	950 × 590	25	75	7	368
BEE22–06	950 × 590	25	75	12	570
BEE22–07	950 × 590	25	75	16	620
BEE22–08	950 × 590	25	75	18	439
BEE22–09	950 × 590	25	75	26	561
BEE22–10	950 × 590	25	250	36	2482
BEE22–11	950 × 590	25	75	12	356
BEE22–12	810 × 430	25	250	21	1973
BEE22–13	950 × 600	25	258	60	6462
BEE22–14	950 × 600	25	360	141	8944
BEE22–15	950 × 600	25	240	90	3093
BEE22–16	950 × 600	25	254	139	3770

In Table 2, we report the quantitative results obtained by our method on BEE22–12, BEE22–13, and BEE22–16 and compare them with the other methods [20,25,52-54]. In the same scenario, our IDF1 and MOTA metrics are optimal, which shows the superiority of our algorithm. Additionally, as the difficulty of the scene increases, the corresponding indicators decrease, which also shows that in difficult scenes, the tracking accuracy of the algorithm will be reduced due to the increase in the number of bees, and the fast-moving speed, and the severe occlusion.

To more intuitively reflect the algorithm performance, we integrated the indicators of all scenarios, As shown in Table 3, our method obtained the most advanced results, and the measured value of IDF1 increased by 8.2 % compared with the ByteTrack. This shows that our method can achieve strong performance in identity retention, which we attribute to DeepSORT. Moreover, the measured value of MOTA also increased by 5.4 %, which is much higher than the previous method, which indicates that the tracking accuracy of our method is optimal. In addition, our method has also achieved good results in MOTP, MT, ML, FP, FN, and Time, and realized real-time function, which indicates that the multi-bee tracking algorithm proposed by us can accurately monitor the status of bees in real-time under the real hive scene.

Additionally, as shown in Fig. 8, the visualization results of our algorithm results in different scenarios. Different bees are marked with different color boxes, and each bee is assigned a unique ID. the curve in

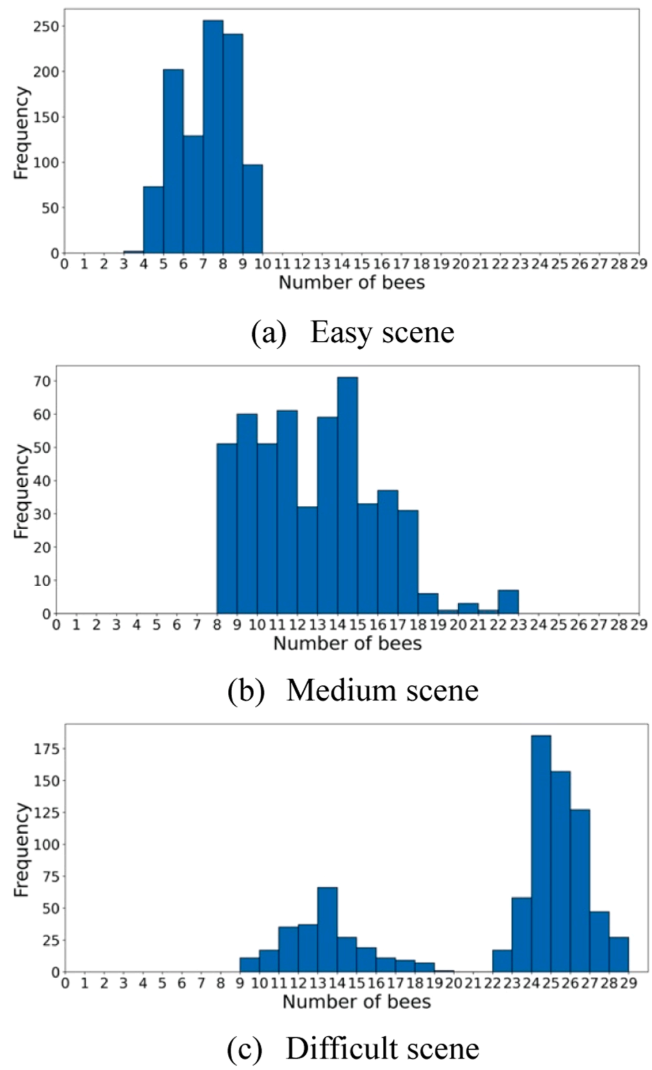


Fig. 7. Distribution of bee population in different scenarios.

the figure is the trajectory of the algorithm tracking bees. as shown in Fig. 8(a), in an easy scene, there are fewer bees and the movement is not intense, so the trajectory curve is short; as shown in Fig. 8(b), in the medium scene, the number of bees increases, and the movement trajectory of bees can be accurately tracked; as shown in Fig. 8(a) in the difficult scene, the number of bees is the largest and the motion is complex. The track line loss is caused by the error of the algorithm. It can be seen in the figure that our algorithm can accurately track bees in various scenarios, laying a solid foundation for the following statistics of the number of bees.

3.4.2. Evaluation of counting algorithms

To explore the accuracy of bee number statistics, we use the previous counting algorithm to count the number of bees that enter and leave the beehive in the current frame scene. Then we calculate the root mean square error (RMSE) between it and the real quantity. RMSE can reflect the degree of difference between the two samples. The smaller the value of RMSE, the closer the predicted result of the algorithm is to the result of manual marking, that is, the higher the accuracy.

Table 4 compares the statistical results of each algorithm in the bee test set. From the table it can be seen that almost all the indicators of our algorithm are optimal in different scenarios, indicating the superiority of our algorithm. Additionally, as the difficulty of the scene increases, each indicator increases continuously, which is also consistent with the tracking results of the previous algorithm in different scenarios. Moreover, in the overall case, the counting error of bees entering the nest is the smallest, and the counting error of bees leaving the nest is the largest.

3.5. Influence of environmental factors on the activity of bee colony

According to the previous analysis of the statistical results of the number of bees, we use the two indicators of the number of bees in the scene and the number of bees entering the nest to measure the active state of the bee colony, which are called overall activity and foraging activity respectively. The factors that characterize the state of the environment around the hive include temperature, humidity, and sound in the center of the hive at different locations of a beehive.

3.5.1. Activity of bees at different times of the day

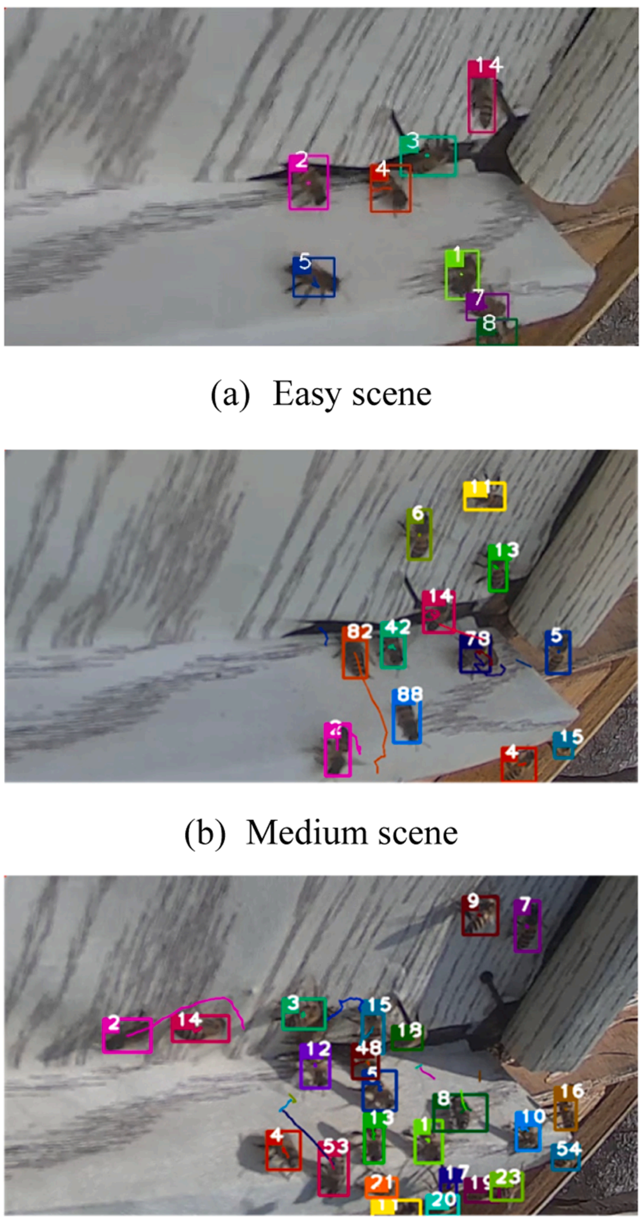
First, we analyze the active state of the bee colony at different times of the day, in which the overall activity takes the average hourly value. The foraging activity takes the cumulative hourly value, as shown in Fig. 9, the abscissa represents different times of the day, the left and dark blue boxes on the ordinate represent the overall activity of bees at the same time of the day (30 days in total), and the right and blue boxes on the ordinate represent the foraging activity The red line in the box represents the median number of bees, the horizontal line above represents the upper limit of the number of bees at that time, the horizontal

Table 2
Performance compared to other algorithms in different scenarios. The number of seeds for each group of models ranges from 50 to 59, and the standard deviation ± st. dev is calculated based on the results of these 10 groups. Our methods outperform all methods on this benchmark (↑ mean higher is better, ↓ mean lower is better).

Scene	Methods	IDF1↑	MT↑	ML↓	FP↓	FN↓	IDs↓	MOTA↑	MOTP↑	Time(ms)
Easy	GMM+KF	5.0 ± 0.5	1.0 ± 0.0	13.3 ± 0.5	570.4 ± 18.2	1891.9 ± 6.1	9.6 ± 1.8	−26.4	57.0 ± 0.3	1.0 ± 0.0
	YOLO+KF	36.5 ± 5.1	17.6 ± 0.5	0.0 ± 0.0	241.7 ± 21.4	90.1 ± 18.1	234.3 ± 15.9	71.3 ± 2.1	82.7 ± 0.5	22.0 ± 1.0
	CTracker	62.4 ± 3.2	7.0 ± 1.1	0.0 ± 0.0	20.0 ± 6.1	956.0 ± 15.1	67.0 ± 6.2	63.4 ± 1.1	66.5 ± 0.1	20.0 ± 0.2
	FairMOT	77.3 ± 2.5	4.0 ± 2.2	0.0 ± 0.0	12.0 ± 8.4	654.0 ± 8.1	43.0 ± 8.3	75.3 ± 0.8	72.4 ± 0.1	57.0 ± 0.3
	ByteTrack	83.6 ± 1.6	8.0 ± 1.1	0.0 ± 0.0	11.0 ± 9.1	154.0 ± 7.5	54.0 ± 3.1	86.4 ± 1.3	87±0.6	22.0 ± 2.0
	Ours	93.0 ± 1.2	18.9 ± 0.3	0.0 ± 0.0	31.7 ± 3.1	48.0 ± 6.1	55.7 ± 2.6	93.2 ± 0.3	79.9 ± 0.2	50.0 ± 4.0
Medium	GMM+KF	0.8 ± 0.4	2.0 ± 0.0	50.1 ± 0.3	1472.6 ± 114.1	6417.5 ± 21.8	10.6 ± 6.1	−23.8	62.8 ± 0.8	5.0 ± 0.0
	YOLO+KF	29.5 ± 3.3	35.7 ± 2.3	4.8 ± 0.6	641.5 ± 78.1	696.5 ± 88.0	1043.5 ± 76.8	61.3 ± 2.7	75.2 ± 0.7	38.0 ± 2.0
	CTracker	50.2 ± 2.6	12.0 ± 0.2	6.0 ± 0.1	96.0 ± 5.8	1365.0 ± 9.4	121.0 ± 5.1	54.2 ± 1.2	56.2 ± 1.3	54±1.1
	FairMOT	67.6 ± 2.1	11.0 ± 0.3	23.0 ± 1.1	65.0 ± 6.1	1251.0 ± 5.3	76.0 ± 6.4	59.3 ± 1.1	57.2 ± 1.3	159±6.1
	ByteTrack	70.6 ± 3.2	11.0 ± 0.8	5.0 ± 0.8	201.0 ± 5.7	763.0 ± 3.8	102.0 ± 5.7	77.4 ± 1.8	76.1 ± 1.2	147±8.2
	Ours	80.7 ± 1.8	41.2 ± 1.4	1.2 ± 0.9	351.3 ± 20.1	421.5 ± 23.5	120.2 ± 4.9	86.2 ± 0.6	75.9 ± 0.3	78.0 ± 7.0
Difficult	GMM+KF	2.0 ± 0.3	0.0 ± 0.0	68.6 ± 2.0	1050.2 ± 63.9	3706.7 ± 13.8	14.7 ± 3.7	−28	61.3 ± 0.4	3.0 ± 0.0
	YOLO+KF	25.1 ± 2.2	62.6 ± 1.6	0.0 ± 0.0	665.8 ± 45.1	393.1 ± 38.5	985.5 ± 34.2	45.8 ± 2.4	78.6 ± 0.8	28.0 ± 2.0
	CTracker	48.2 ± 4.1	16.0 ± 0.4	12.0 ± 0.2	113 ± 5.1	2910.0 ± 12.2	249.0 ± 6.7	51.1 ± 2.2	49.9 ± 2.1	26.0 ± 5.1
	FairMOT	64.2 ± 2.1	13.0 ± 1.5	30.0 ± 1.2	103.0 ± 6.1	2313.0 ± 16.1	104.0 ± 9.4	52.4 ± 2.1	60.2 ± 1.9	87.0 ± 3.2
	ByteTrack	64.5 ± 3.5	18.0 ± 2.1	11.0 ± 0.2	275.0 ± 12.5	1238.0 ± 23.7	209.0 ± 12.1	74.2 ± 1.8	74.2 ± 3.1	30.0 ± 5.2
	Ours	71.0 ± 0.8	66.7 ± 1.1	0.0 ± 0.0	347.7 ± 42.5	335.2 ± 34.9	308.9 ± 6.5	73.7 ± 2.0	78.3 ± 0.3	60.0 ± 6.0

Table 3
Combining different scenarios to compare the performance of other algorithms.

Methods	IDF1↑	MT↑	ML↓	FP↓	FN↓	IDs↓	MOTA↑	MOTP↑	Time(ms)
GMM+KF	1.9 ± 0.2	3.0 ± 0.0	132.0 ± 2.5	3093.2 ± 181.5	12,016.1 ± 39.3	34.9 ± 10.1	−25.4	59.8 ± 0.7	3.0 ± 0.0
YOLO+KF	29.3 ± 1.9	115.9 ± 3.1	4.8 ± 0.6	1549.0 ± 71.1	1179.7 ± 103.0	2263.3 ± 75.5	59.1 ± 1.5	77.5 ± 0.5	30.0 ± 2.0
CTracker	52.4 ± 1.8	35.0 ± 6.0	18.0 ± 2.0	229.0 ± 92.0	5231.0 ± 257.0	437.0 ± 16.0	55.1 ± 2.1	56.2 ± 1.5	33.0 ± 0.4
FairMOT	68.4 ± 1.5	28.0 ± 3.0	53.0 ± 2.0	180.0 ± 32.0	4218.0 ± 32.0	223.0 ± 14.0	61.2 ± 1.7	62.1 ± 1.6	101.0 ± 0.7
ByteTrack	71.5 ± 1.6	37.0 ± 1.0	16.0 ± 3.0	487.0 ± 42.0	2155.0 ± 31.0	365.0 ± 8.0	78.1 ± 0.7	78.5 ± 1.3	66.0 ± 0.8
Ours	79.7 ± 1.0	126.8 ± 1.4	1.2 ± 0.9	730.7 ± 51.8	804.7 ± 40.0	484.8 ± 9.7	83.5 ± 0.7	77.3 ± 0.2	63.0 ± 4.0



(a) Easy scene

(b) Medium scene

(c) Difficult scene

Fig. 8. Visualize the algorithm results.

line below represents the lower limit of the number of bees at that time, and the length of the box represents the distribution of the number of bees at that time. The overall activity of the bee colony and the foraging activity within a day tend to be more consistent, both starting to be active at 5:00 in the morning. The activity gradually increased, reaching a peak at 11:00 (the overall activity 3.3 ± 1.3, foraging activity 713.8 ± 435.4), and then the activity began to gradually decrease, and the activity of the colony basically dropped to 0 after 18 o'clock in the evening. It should be noted that the overall activity at night is not 0, which is caused by the false detection of the background by the algorithm. During the experiment, the local sunrise time in Fuzhou was in the range of 5:57 to 6:26, and the sunset time was in the range of 18:04 to 18:18. Therefore, we divided the time between 5:00 in the morning and 6:00 p.m in the evening into the daytime, and the rest nighttime. We conducted *t*-test on the activity of day and night, and the statistical results showed that the bee colony had a strong circadian rhythm (n = 696, foraging activity: $t < 0.05$ (t = 2.27e-57), the overall activity: t = 2.05e-49), that is, bees work during the day and rest at night. Additionally, we found that on different days, whether it is the overall activity or the foraging activity, the difference at the same time is relatively large, which may be caused by the change of the environmental state around the beehive, We also got similar conclusions in Fig S6. And previous studies have concluded that bee activity is usually affected by weather conditions [45,46].

3.5.2. *Activity of bees in different weather*

The influence of different weather on the activity of bees in a month, The abscissa represents the date, the left side of the ordinate, and the blue line represent the overall activity of bees. We accumulate the average number of bees per hour in the current scene. The right side of the ordinate and the green line indicate the foraging activity, and the bees entering the hive every hour are accumulated. On the top of the abscissa, we use boxes of different colors to represent different types of weather. Through our observation, there are 6 kinds of weather changes this month. The colors from light to dark respectively represent sunny, cloud, overcast sky, light rain, moderate rain, and heavy rain.

Therefore, we need to explore the relationship between environmental changes and bee colony activity. We first used the local weather forecast in Fuzhou to analyze the influence of weather conditions on the activity of bee colonies. During the experiment, the local weather conditions include sunny, cloudy, overcast, light rain, moderate rain, and heavy rain (It should be noted that these conditions refer to the Chinese national standard GB/T35224–2017). For the overall activity of the bee colony, we take the hourly average, and the foraging activity takes the cumulative value of the day, as shown in Fig. 10, The abscissa represents the date, the left side of the ordinate, and the blue line represent the overall activity of bees. We accumulate the average number of bees per hour in the current scene. The right side of the ordinate and the green line indicate the foraging activity, and the bees entering the hive every hour are accumulated. On the top of the abscissa, we use boxes of different colors to represent different types of weather. Through our observation, there are 6 kinds of weather changes this month. The colors from light to dark respectively represent sunny, cloud, overcast sky, light rain, moderate rain, and heavy rain.

According to Fig. 10, the overall activity and foraging activity of bee colonies on rainy days are significantly lower than those in other weather conditions, such as rain on March 7, the overall activity and foraging activity of bee colonies were the lowest in a month, at 2 and 2097, respectively. On March 13, it was sunny, and the overall activity and foraging activity of the colony was the highest, at 3 and 15,580, respectively, similar conclusions were obtained in Fig S7. And a similar

Table 4
Compare the counting accuracy of other algorithms. Use our counting algorithm to count the tracking results of other algorithms, and use RMSE for evaluation. The smaller the RMSE means the better the counting performance. In different scenarios, C, E and O are used as parameters to measure the activity of bees (C represents the current number of bees at the entrance of the nest, E represents the number of bees entry the beehive, and O represents the number of bees out the beehive), and the final summary is overall.

Methods Scene		GMM+KF	YOLO-tiny+KF	CTracker	FairMOT	ByteTrack	Ours
Easy scene	C	30.2 ± 0.8	2.5 ± 0.3	3.2 ± 0.1	1.2 ± 0.3	0.7 ± 0.2	0.1 ± 0.0
	E	0.0 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
	O	0.16±0.0	0.1 ± 0.0	0.1 ± 0.0	0.2 ± 0.0	0.2 ± 0.0	0.2 ± 0.0
Medium scene	C	373.0 ± 19.3	37.5 ± 1.1	42.3 ± 0.5	20.1 ± 0.4	8.4 ± 0.6	1.0 ± 0.2
	E	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.2 ± 0.0	0.2 ± 0.0
	O	0.7 ± 0.1	0.9 ± 0.2	0.8 ± 0.1	0.7 ± 0.2	0.8 ± 0.1	0.8 ± 0.1
Difficult scene	C	115.2 ± 6.8	8.8 ± 1.5	10.4 ± 0.8	6.3 ± 0.4	4.7 ± 0.1	1.6 ± 0.2
	E	0.2 ± 0.0	0.2 ± 0.0	0.2 ± 0.0	0.2 ± 0.0	0.3 ± 0.0	0.3 ± 0.0
	O	0.5 ± 0.0	0.8 ± 0.2	0.6 ± 0.1	1.2 ± 0.1	2.5 ± 0.2	3.7 ± 0.2
Overall	C	174.6 ± 8.8	6.3 ± 0.6	9.5 ± 1.0	5.2 ± 0.2	2.8 ± 0.4	1.3 ± 0.1
	E	0.1 ± 0.0	0.1 ± 0.0	0.1 ± 0.0	0.2 ± 0.0	0.2 ± 0.0	0.2 ± 0.0
	O	0.4 ± 0.0	0.6 ± 0.1	0.5 ± 0.0	0.9 ± 0.0	1.2 ± 0.2	1.6 ± 0.1

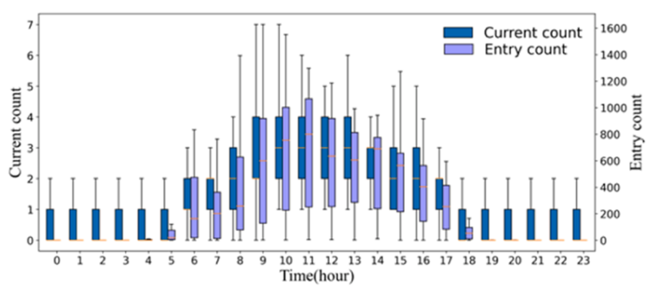


Fig. 9. The activity level of the bee colony at different times of the day.

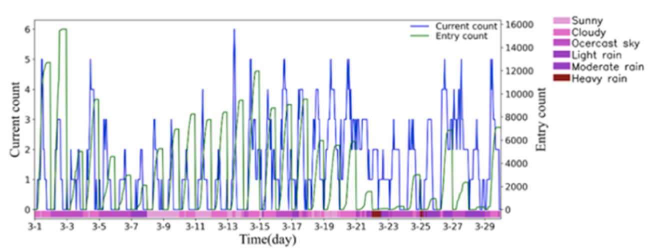
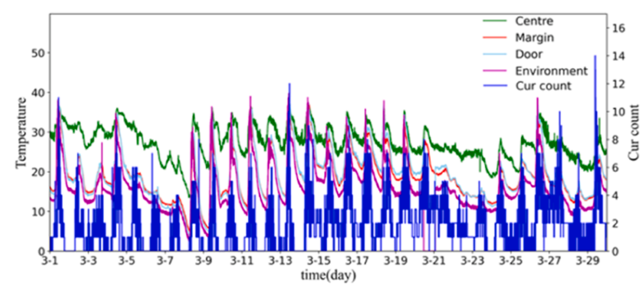


Fig. 10. The influence of different weather on the activity of bees in a month.

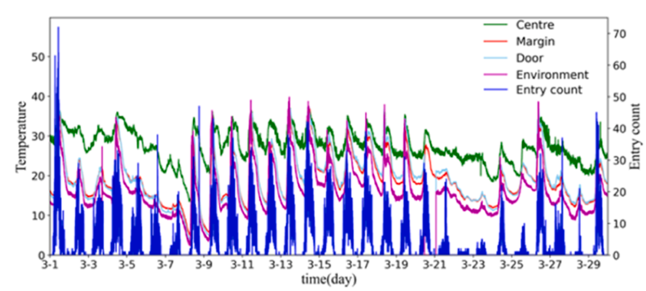
phenomenon was found by Lawson and Rands et, al. [47].

3.5.3. Activity of bees at different temperatures

The above analysis begs the question of what factors account for differences in colony activity on days when it is not raining. To answer this question, we need to analyze the temporal relationship between the three environmental factors of temperature, humidity, and sound and the activity of the bee colony. as shown in Fig. 11, the right side of the longitudinal coordinates represents temperature, and we take the mean temperature per minute, with green, red, light blue, and purple curves representing the temperature of the hive center, margin, door, and environment, respectively. (a) The blue curve represents the bee's overall activity, taking the average of each hour, and (b) the blue curve represents the bee's foraging activity, taking the cumulative value of each hour. It can be seen from the observation that: (1) The temperature fluctuation range at the center of the nest is small, and the daily temperature upper and lower limits and fluctuation trends are stable after March 9, ranging from 18.47 to 36.94 °C. This is since the beehive's Internal hive temperature as a means of monitoring honey bee colony health in a migratory beekeeping operation before and during winter [38], and before March 9, due to The outside temperature is low, and the heating capacity of the bee colony in the beehive is limited [48], so the temperature fluctuation in the center of the comb is relatively large, between 13.47 and 36.67 °C; (2) The temperature change trends of the other three locations are the same. Among them, the external ambient temperature of the beehive is the lowest. We take the external temperature as the independent variable and use the temperature at the door of the nest and the temperature at the margin of the nest as the dependent variables for linear regression. As shown in Fig. 12(a), we get two linear relationship expressions: $y = 1.07x+2.02$ ($R^2=0.94$) and $y = 0.97x+3.32$ ($R^2=0.93$), that is, the base temperature of the nest door and edge temperature is 2.02 and 3.32 °C higher than the external

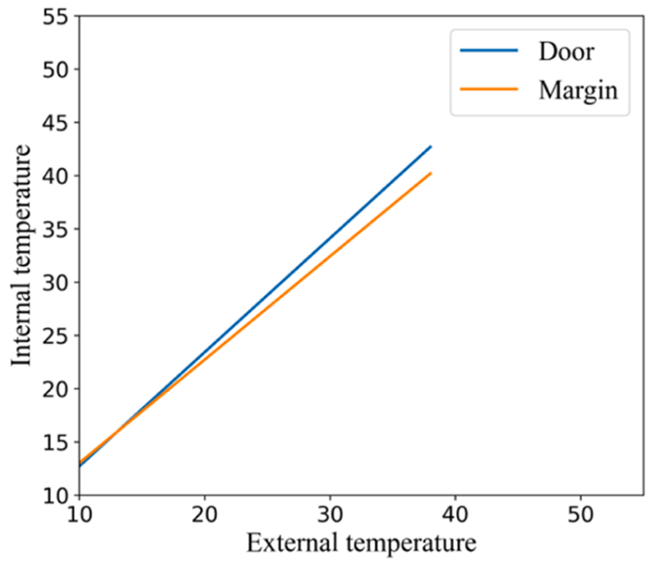


(a) The relationship between the temperature at different positions of the beehive and the overall activity of the bee colony.

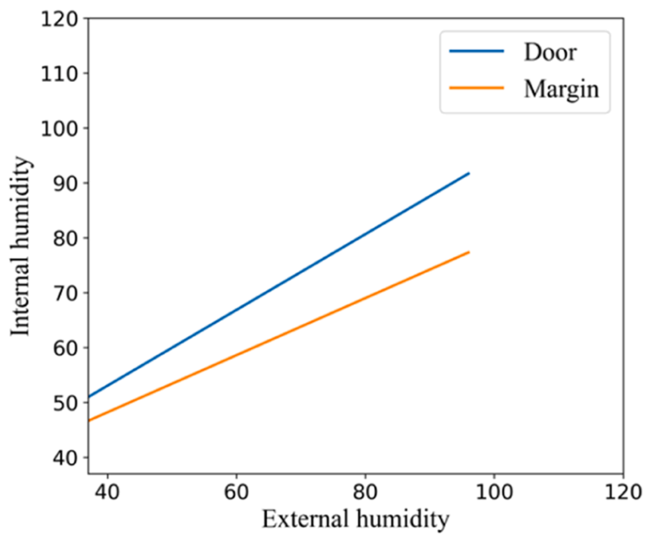


(b) The relationship between the temperature at different positions of the beehive and the foraging activity of bee colonies.

Fig. 11. Effect of temperature change on hive activity in different parts of hive.



(a) Temperature linear regression.



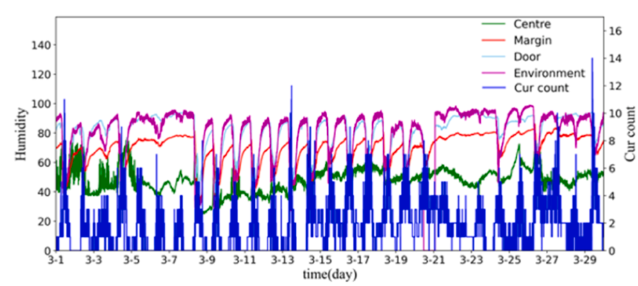
(b) Humidity linear regression.

Fig. 12. Linear regression between external temperature and humidity and the temperature and humidity at the door and margin of the nest.

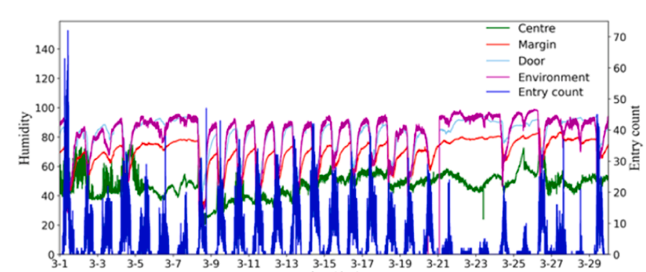
temperature, and the external temperature per liter. When the temperature is 1 °C higher, the temperature at the entrance and edge of the nest increases by 1.07 and 0.97 °C, respectively, which also shows that the interior of the hive, as an almost closed space, can play a role in thermal insulation to a certain extent; (3) It is difficult to see the effect of temperature on colony activity at the center of the nest, while the temperature monitored at the other three locations on some days, the higher the daytime temperature, the higher the overall colony activity and foraging activity. But there are exceptions, such as March 10 and March 12 reflect the opposite conclusion, which may be due to other factors, namely that temperature can only partially reflect the active state of bee colonies [25], consistent with this conclusion in Fig S8(a) and Fig S8(b).

3.5.4. Activity of bees with different humidity

Abrol and others found that humidity has an effect on the active state of bee colonies and showed a certain negative correlation [49]. Therefore, we analyzed the effect of humidity changes at different positions of the beehive on the activity of the bee colony, in which the humidity of each position was taken as the average value of every minute, and the overall activity of the bee colony and the degree of foraging activity was taken as the average value of each hour, as shown in Fig. 13, the right side of the longitudinal coordinates represents humidity, and we take the mean temperature per minute, with green, red, light blue, and purple curves representing the humidity of the hive center, margin, door, and environment, respectively. (a) The blue curve represents the bee's overall activity, taking the average of each hour, and (b) the blue curve represents the bee's foraging activity, taking the cumulative value of each hour. It can be seen from observation: (1) The humidity at the center of the nest is the lowest and the fluctuation range is the smallest, and the daily change trend after March 9 is relatively regular, basically between 23 and 73 %, while the larger fluctuations on the previous days are because these days are cloudy and rainy (see Fig. 10), so the humidity is naturally higher; (2) The humidity changes in the other three locations are consistent, and the closer to the center of the nest during the day, the higher the humidity is, and the opposite is true at night. We take the external humidity as the independent variable and do linear regression with the humidity at the door of the nest and the humidity at the margin of the nest respectively. As shown in Fig. 12(b), we get two linear relationship expressions: $y = 0.69x+25.45$ (R^2=0.82) and $y = 0.52x+27.4$ (R^2=0.73), that is, the basic humidity of the nest door and edge humidity is 25.45 % and 27.4 % higher than the external humidity, and for every 1 % increase in the external humidity, the nest door and edge humidity are increased by 0.69 % and 0.52 %, respectively. It shows that the beehive structure has a certain influence on the humidity; (3) Before March 9, except for the center of the hive, the lower the daytime humidity monitored in the other three locations, the higher the overall activity of the colony and the feeding activity is higher, and after March 9, since the changes of humidity in each location are relatively stable on different days, it is difficult to judge their impact on the activity of the bee colony. Fig S8(c), Fig S8(d) also obtained corresponding conclusions.



(a) Relationship between humidity and overall bee colony activity.



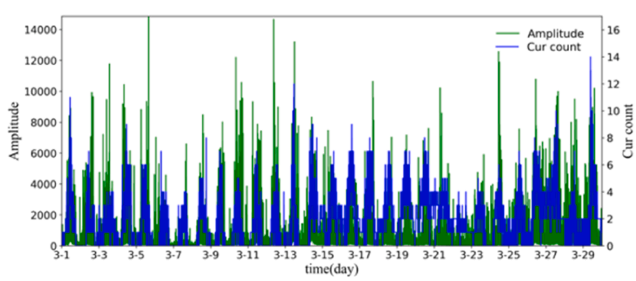
(b) Relationship between humidity and bee colony foraging activity.

Fig. 13. Effect of humidity change on hive activity in different parts of hive.

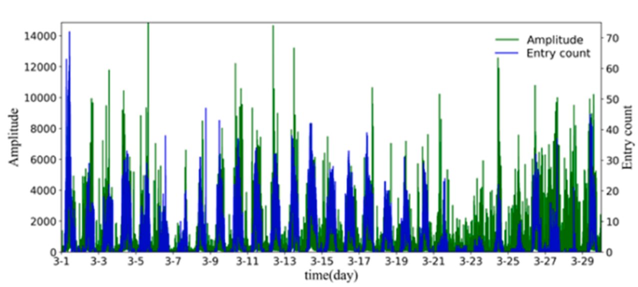
3.5.5. Relationship between sound and bee activity

Next, we also analyzed the relationship between the sound changes at the center of the beehive and the bee colony activity, in which the maximum value per minute was taken for the sound, and the hourly average was taken for the overall bee colony activity and foraging activity, as shown in Fig. 14, the abscissa represents the date, the left side of the coordinate axis and the green curve represent the amplitude of the sound, the right side of the coordinate axis and the blue line in (a) represent the overall activity of bees, and the right side of the coordinate axis and the blue line in (b) represent the foraging activity of bees. Through observation, it can be seen that on most days, the sound at the center of the comb increases with the overall activity and foraging activity of the colony. When the colony is inactive, the sound at the center of the comb also increases lower, but there are still some days, such as March 10, when the sound is higher during the day, but the overall activity of the bee colony is lower. We took the sound amplitude as the independent variable and the activity as the dependent variable and established a linear regression model for fitting, and the relationship was obtained as $y = 0.0044x+1.58$ (R^2=0.05), This regression equation also verifies our observation, but the linear relationship between them is weak due to other environmental factors. We also found a similar conclusion in Fig S9. In previous work, Kulyukin et al. also found a certain relationship between acoustic signals and colony activity [50].

Through the above analysis of the impact of different environmental factors and bee colony activity, we found that changes in temperature, humidity, and sound will have a certain impact on bee colony activity, but each factor can only reflect colony activity in some cases, which means that the bee colony activity should be affected by a variety of environmental factors. Nha Ngo et al. used the ANOVA method and found that different environmental variables have a certain impact on honey bee activity [25].



(a) Relationship between sound and overall bee colony activity.



(b) Relationship between sound and bee colony foraging activity.

Fig. 14. Effects of sound changes at the center of a beehive on the activity of bee colonies.

3.5.6. Analysis of multiple factors and bee activity

Therefore, we need to analyze these environmental factors together to further reveal the relationship between the environment and bee colony activity. In addition, considering that the colony has a circadian rhythm, that is, no matter how the nighttime environment changes, it does not affect the activity of the colony, so we should only keep the period when the colony is active during the day. According to the local sunrise and sunset times in Fuzhou during the experiment provided above, we will only analyze the data from 6:00am to 6:00pm. We select two factors to analyze the relationship between the temperature, humidity, and sound and the activity of bees in three environments. Take the graph in the upper left corner of Fig. 15(a) as an example, and the abscissa is T_Center (cur), indicating the temperature in the center of the hive, cur in brackets indicates that the current analysis is the overall activity of bees, and the ordinate H_Center(cur) indicates the humidity in the center of the hive. Each point in the figure indicates the activity of bees. Dark blue is the lowest and red is the highest. Please refer to the color chart on the right. These figures show the center, edge, doorway, and environment of the hive from left to right. H represents humidity, T represents temperature, and sound represents the sound amplitude Fig. 15(a) Analyze the relationship between the three environmental factors and the overall activity of bees, Fig. 15(b) analyze the relationship between the three environmental factors and the foraging activity of bees. After observation, we found the following findings: (1) Under the premise that the sound amplitude at the center of the comb is between 500 dB and 2000 dB, the temperature and humidity of different positions of the beehive have a range, which makes the overall activity of the bee colony and the Foraging activity is relatively high. Abou-Shaara and others [51] also believed that the bee colony could maintain a high activity level under a wide range of environmental conditions; (2) Outside the hive, the temperature was 19 °C~40 °C and the humidity was 27 %~63 %, as the temperature increases and the humidity decreases, the overall activity and foraging activity of the bee colony will increase; (3) Similarly, at the door of the beehive, the suitable temperature is 20 °C~37 °C, the humidity is 40 %~73 %; at the edge of the comb inside the beehive, the suitable temperature is 20 °C~37 °C, and the humidity is 47 %~80 %; in the center of the beehive, the suitable temperature is 25 °C~37 °C, humidity is 48 %~67 %; (4) Additionally, we found that the closer to the center of the comb, the suitable temperature, and humidity range are constantly increasing, which is consistent with the above analysis on the conclusion that humidity affects the temperature and humidity of different positions. We found similar conclusions in Fig S10.

4. Conclusion

In this paper, we construct the BEE22 dataset, which can realistically reflect the scene of bees entering and leaving the hive. At the same time, based on this dataset, compared with existing methods, the proposed multi bee tracking algorithm can effectively solve the problems of mutual occlusion and ID switching among bees. Specifically, we achieved 83.5 % ± 0.7 % MOTA, 77.3 % ± 0.2 % MOTP, and 79.7 % ± 1.0 % IDF1, this performance evaluation demonstrates that our method exhibit high performance and yield acceptable results for multi-object tracking tasks. Furthermore, using our bee counting algorithm to count the tracking results of each model, the RMSE for current, entry, and out scene reached 1.3 ± 0.1, 0.2 ± 0.0, and 1.6 ± 0.1, respectively. From the result it can be seen that almost all the indicators of our algorithm are optimal in different scenarios. Afterwards, through monitoring the real environment of bees, it was found that their attendance decreased during heavy rainfall weather. the activity of the bee colony will also increase accordingly, when the amplitude is 500 dB to 2000 dB, the temperature of the center of the beehive is 25 °C to 37 °C, and the humidity is 48 % to 67 %. Ultimately, our system provides a reliable tool for researchers while making it easier for beekeepers to manage their hives.

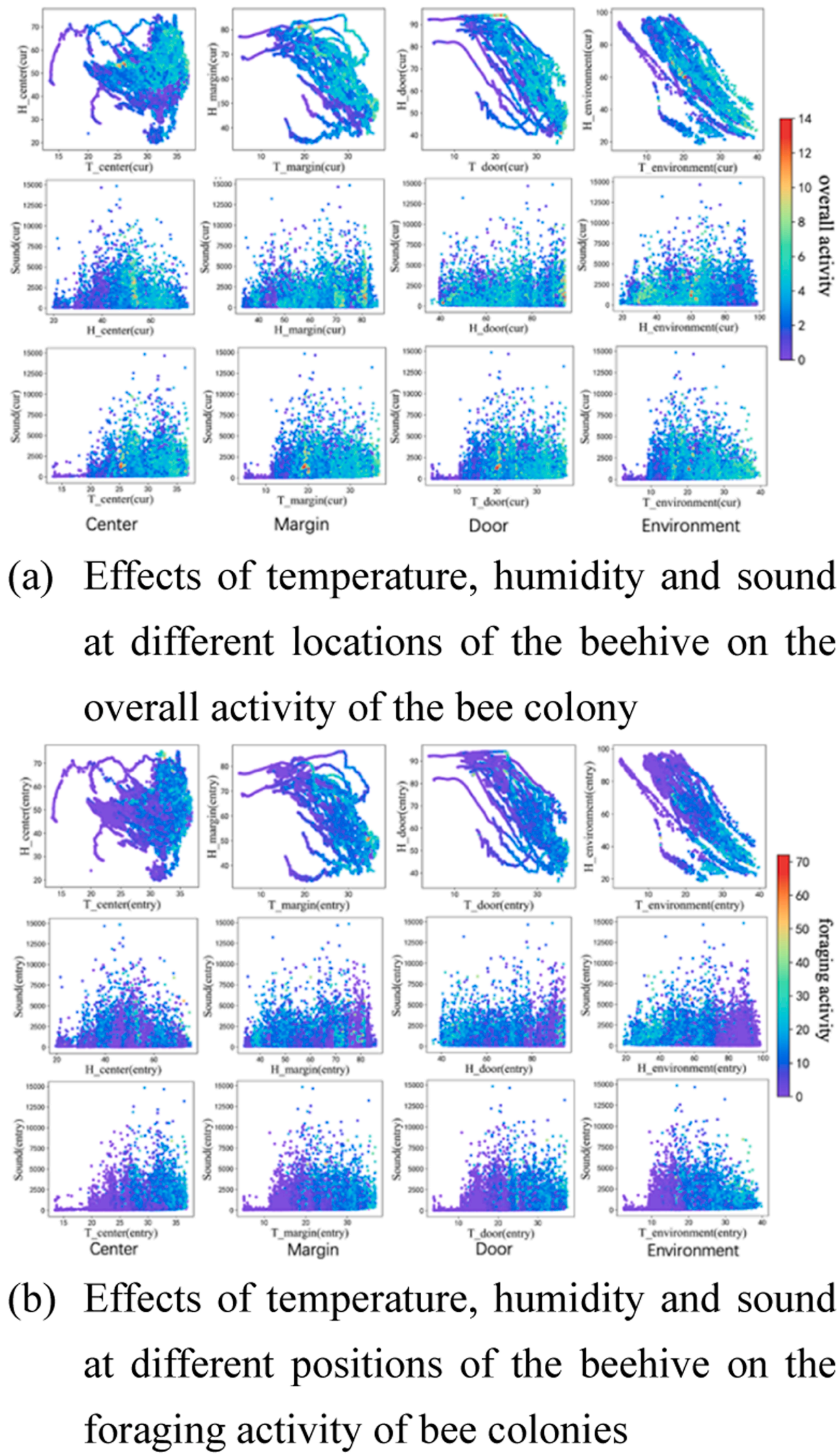


Fig. 15. The relationship between temperature, humidity, and sound and the activity of bees.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

CRediT authorship contribution statement

Yiyao Zheng: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Xiaoyan Cao:** Writing – review & editing, Methodology, Data curation. **Shaocong Xu:** Software, Data curation. **Shihui Guo:** Supervision, Funding acquisition. **Rencai Huang:** Data curation. **Yingjiao Li:** Data curation. **Yijie Chen:** Data curation. **Liulin Yang:** Methodology. **Xiaoyu Cao:** Methodology. **Zainura Idrus:** Formal analysis, Methodology, Supervision, Visualization. **Hongting Sun:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2024.100584.

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