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RESEARCH ARTICLE

IgnitusTracker: Tracking Bee Flights for Assessing the Activity of *Bombus Ignitus* Towards Keeping Optimal Pollination Environments

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ABSTRACT *Bombus ignitus* plays a vital role as a pollinator insect in greenhouse horticulture in Japan, China, and Korea. The activity of worker bees diminishes over time, prompting the replacement of the entire hive with new bees. However, considering the cost of hives, it is imperative to pinpoint the optimal replacement timing, balancing the decline in bee activity and the expenses associated with hive renewal. In pursuit of this goal, Calculating the ideal timing for replacement using activity data is preferable. Currently, Farmers often rely on visual monitoring and empirical judgments to decide when to replace hives due to the unavailability of activity data. Addressing this gap, Our study focuses on accurately quantifying the arrivals and departures of *Bombus ignitus* males and workers from hives, using these metrics as reliable indicators of bee activity. For this purpose, we propose a method for accurately tracking *Bombus ignitus*. Our proposed method combines specialized tracking techniques for honeybees, drawn from existing research, with commonly used tracking methods for pedestrians and automobiles. The evaluation of our method using test data showcases superior tracking precision with reduced errors, providing a more accurate tally of arrivals and departures compared to existing approaches. Furthermore, when applied on actual farms, our method revealed a significant decrease in worker bee arrivals and departures as the expected replacement time, based on farmers' experience, drew nearer. This promising result suggests that our approach facilitates data-informed decision-making. As a result, our findings pave the way for significantly enhanced efficiency and precisely timed hive replacements, supported by compelling evidence, thus shaping the future landscape of beekeeping practices.

INDEX TERMS Bee tracking, computer vision, machine vision, pollination management, smart agriculture.

I. INTRODUCTION

Pollinator insects are used to pollinate crops in greenhouse horticulture. From an environmental protection standpoint, bumblebees indigenous to specific regions are employed for this purpose in many parts of the world [1]. In Japan, China, and Korea [2], [3], the indigenous *Bombus ignitus* (*B. ignitus*), a bumblebee species, is utilized for pollination [1], [4], [5], [6]. Crop pollination in greenhouse horticulture is facilitated by installing hives containing *B. ignitus*. Hive replacement is determined based on the activity of worker bees, which play a vital role in pollination. However, this activity diminishes over time according to the hive's lifecycle. As the end of the lifecycle nears, there is a known shift where the number of worker bees decreases while that of male bees increases. This highlights the importance of monitoring the activity of both worker and male bees when deciding when to replace the hives. On actual farms, due to the expense of hives, replacements are usually made based on farmers' empirical judgments. They consider both the decline in activity and the costs associated with replacement. The first method involves confirming activity levels by observing bite

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marks that result from *B. ignitus* worker bees biting during pollination. When bite marks become scarce, it indicates insufficient worker bee activity and suggests that it is time for hive replacement. However, this approach leads to reduced worker activity until the new hives arrive, as there is a delay in their delivery. Consequently, this method can result in inadequate crop pollination and economic losses. The second method involves directly opening the hive to assess the life cycles of worker and male bees. While this method is reliable, conducting individual hive checks on large farms with multiple hives is labor-intensive. Relying solely on empirical judgments based on farmers' visual observations does not guarantee optimal hive replacement timing and it's challenging for new farmers with limited experience. Making data-driven decisions becomes indispensable to ensure hive replacement occurs at the right time. However, the first step involves accurately quantifying the activity of *B. ignitus* males and worker bees. In order to count bee activity in terms of arrivals at and departures from the hive, tracking methods can be used on the video acquired from a camera attached to the hive. However, existing methods don't accurately track *B. ignitus*, resulting in inaccurate counts.

The main objective of this paper is to accurately count the number of arrivals and departures of *B. ignitus* males and worker bees at the hive as a measure of their activity. We propose a tracking method for *B. ignitus* to achieve accurate counting of arrivals and departures that draws from existing techniques specialized for honeybee, pedestrian, and automobile tracking. The contributions of this study are outlined below.

- To achieve precise counting of arrivals and departures, taking into account the unique behavioral traits of *B. ignitus*, we proposed a tracking technique tailored to the species. This method draws inspiration from both bee-specific tracking approaches and tracking methods applicable to non-bee subjects.
- The complete procedure for counting the arrivals and departures of *B. ignitus* male and worker bees at the hive, employing a video-based tracking methodology, is illustrated below.
- To compare with farmers' experiential decisions regarding hive replacement timing, we strategically positioned cameras on farms to meticulously record the arrivals and departures of *B. ignitus* bees at the hive.

Based on the results of this study, it is expected that this research could reduce the labor required for pollination management on expansive farms and facilitate effective pollination management for novice farmers.

II. RELATED WORKS

A. BEE ACTIVITY MANAGEMENT

Numerous studies have been conducted to analyze bee behavior based on data collected from various sensors. For example, researchers have employed Radio Frequency Identification (RFID) tags attached to bees to conduct individualized behavior analysis using radio waves [7]. However, affixing tags to each bee as they reproduce and new bees emerge proves challenging for farmers to manage effectively. Additionally, investigations have been undertaken using sound data obtained from microphones. Heise et al. [8] utilized frequency and waveform characteristics of bumblebee wing sounds to classify hive arrivals and departures based on audio cues. Nevertheless, using microphones to measure bee activity encounters challenges in distinguishing between wing sounds of multiple individuals and background noises, making it difficult to accurately count the simultaneous arrivals and departures of multiple bees.

Conversely, studies utilizing video data have also been carried out [9], [10], [11]. Magnier et al. [12] proposed a method to extract the movement of bees flying over a white background from camera footage, enabling the counting of their arrivals and departures to and from the hive. Ratnayake et al. [13] visualized honeybee flower visits and foraging time by analyzing flower positions and bee movements in camera videos. These studies utilize videos to measure both bees' visual characteristics and intricate movements. However, while these methodologies can manage the activity of *B. ignitus*, no efforts have been made to separate the activity of male and worker bees. Separately managing the activity of male and worker bees is crucial for estimating the optimal time to replace the hive of *B. ignitus*. In this study, videos are employed to individually quantify the activity of *B. ignitus* males and workers.

B. MULTIPLE OBJECT TRACKING

Multiple Object Tracking (MOT) involves tracing numerous objects within a video, commonly employing the tracking-by-detection approach, which hinges on the Bounding Box (BBox) derived from Object Detection [14], [15], [16], [17]. Numerous tracking techniques utilize the prediction of BBox through the Kalman Filter [18] in advance, subsequently determining object movement trajectories by associating them with the most similar detected BBox. Beyond evaluating solely the BBox similarity, tracking methods have also evolved to incorporate Re-Identification, considering both the BBox and the similarity of appearance features in the captured objects [19], [20], [21], [22], [23]. Notably, BYTE [21], a ByteTrack association approach accounting for BBox confidence scores, excels in accurate object tracking, even in scenes with occlusion where multiple objects overlap. Conversely, Joint Detection and Embedding (JDE), which combines object detection and appearance feature calculation for tracking, has also emerged distinctly from tracking-by-detection. However, applying Re-Identification and JDE for tracking bees is difficult because classified male and worker bees have the same visual appearance in *B. ignitus*. These tracking methods have been primarily studied using datasets centered around pedestrians and automobiles.

Various studies have been conducted on bee tracking. Given the considerable variability in bee movements during tracking [13], a straightforward constant velocity model is used instead of Kalman Filter to predict bee center coordinates in advance [9], [11], [12], [13]. Noteworthy among these methods, Yang and Collins [9] devised an approach to decompose the BBox of individual bees in instances of false detections, where two bees were erroneously included in a single BBox, ensuring accurate tracking of multiple bees. The development of diverse object tracking methodologies [24], [25] has catalyzed research into measuring events transpiring within videos [12], [13], [26], [27]. In this study, a tracking approach is employed to accurately count the arrivals at and departures from the hive for *B. ignitus*, which effectively counts bees entering and leaving the hive. The occurrence of ID switches, indicating bee swaps in tracking, introduces significant counting errors due to one tracking result encompassing the movement trajectories of more than two bees. Consequently, we propose a method grounded in a variety of tracking techniques targeting bees, pedestrians, and automobiles. This method seeks to maintain a low ID-switch occurrence while achieving accurate tracking.

C. CHALLENGES OF TRACKING B. IGNITUS

Three issues inherent in conventional methods must be addressed to achieve an accurate count of bees arriving at and departing from the hive.

The first concern pertains to the fact that the method for calculating similarity in association is not bee-specific. The predominant metrics used include Intersection Over Union (IoU) [21], [28], utilized in pedestrian and vehicle tracking, and pixel distance [9], [13] for bee tracking. IoU is advantageous for linking identical entities as it accounts for the size and shape of two BBoxes. However, if no overlap exists between the BBoxes, the IoU yields a score of zero, regardless of their proximity. Pixel distance, used to measure the distance between the center coordinates of the bees on a frame, avoids a complete score of zero, even without BBox overlap. Yet, when distinct individuals are close, they are erroneously linked since BBox size and shape are not considered. Moreover, neither IoU nor pixel distance is suitable for accurately tracking bees, especially when multiple bees alter their direction rapidly. Therefore, to rectify this, we adopted a similarity metric in this study that can express the distance between BBoxes even without overlap and can also account for BBox size and shape.

The second challenge involves handling false detections where two bees are mistakenly enclosed within a single BBox due to their crossing paths, making it impossible to separate them based solely on detection scores. In situations where two bees should be linked to two separate BBoxes, the presence of only one BBox due to false detection results in the failure to track one of the bees. Yang and Collins [9] termed this occurrence a "merged situation" and introduced a technique to split a single BBox into two. However, their method was based on white backgrounds and background subtraction for bee detection, which did not involve BBox scores. In the realm of object detection, detecting two bees as a single BBox would likely yield a low score for that BBox. While BYTE [21] can consider BBox scores, it does not encompass the idea of dividing false detections. To address this, we have devised an approach that considers BBox scores while effectively splitting a single BBox into two, overcoming the challenge of false detections.

Third, the basic constant velocity model [9], [12], [13] employed in bee tracking methods lacks the capacity to sustain bee tracking when associations with detection outcomes fail. While the Kalman Filter [19], [21], [22], [28], prevalent in pedestrian and vehicle tracking approaches, can utilize past detection results to temporarily continue bee tracking even without current detections, the simple constant velocity model [9], [12], [13] used in bee tracking methods necessitates the presence of detection results to sustain tracking. Therefore, we expanded the basic constant velocity model to enable precise tracking of *B. ignitus*, drawing inspiration from the functionality of the Kalman Filter in established tracking methodologies.

III. IGNITUSTRACKER

In this study, we introduce a novel tracking approach named IgnitusTracker to achieve an accurate count of *B. ignitus* arrivals and departures to and from the hive. Following the tracking-by-detection paradigm, IgnitusTracker takes BBoxes with associated confidence levels as input. It then proceeds to track worker and male bees using IgnitusTracker after their classification through object detection. IgnitusTracker comprises two key components, as illustrated in Fig. 1: IgnitusModel, responsible for overseeing the movement of individual bees, and IgnitusManager, which oversees multiple IgnitusModels.

IgnitusModel extends the simple constant velocity model utilized in bee tracking approaches to encompass the role of the Kalman Filter employed in pedestrian and automobile tracking methods. Meanwhile, IgnitusManager employs the Generalized IoU (GIoU) metric for calculating the similarity between predicted and detected BBoxes. This manager also factors in the score of the detected BBox in merged situations, enhancing accuracy. The k-th frame in the video is denoted as $\mathbf{f}_k$.

A. IGNITUSMODEL

IgnitusModel anticipates the bee's BBox in the subsequent frame and updates the state BBox as a tracking outcome, relying on the detected BBox most similar to the anticipated one. This iterative process is repeated for each frame, ensuring the continuity of bee tracking. We extended the constant velocity model to temporarily update the state BBox from past detection results, such as the Kalman

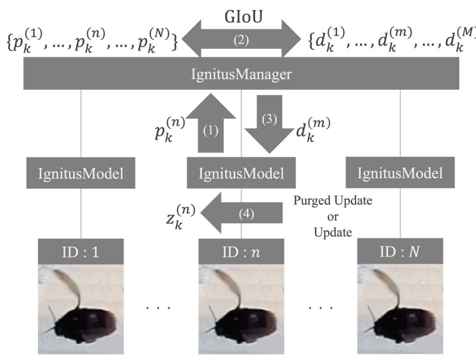


FIGURE 1. Overview of IgnitusTracker. (1) IgnitusManager refers to IgnitusManager's predictions. (2) IgnitusManager calculates the similarity between predictions and detections to associate them.
(3) IgnitusManager assigns detections to individual IgnitusModels.
(4) IgnitusModel updates the state.

Filter, and to decompose the detection results in merged situations.

1) PREDICTION STATE

The predicted center coordinates $(x_k^{\text{pred}}, y_k^{\text{pred}})$ of the bee tracked in the subsequent frame $\mathbf{f}_k$ are determined from the center coordinates of the state BBox in the preceding two frames (Equation 1), akin to the approach used in existing methods [9], [11], [13].

$$\begin{pmatrix} x_k^{\text{pred}} \\ y_k^{\text{pred}} \end{pmatrix} = \begin{pmatrix} 2 & 0 & -1 & 0 \\ 0 & 2 & 0 & -1 \end{pmatrix} \begin{pmatrix} x_{k-1} \\ y_{k-1} \\ x_{k-2} \\ y_{k-2} \end{pmatrix} \tag{1}$$

For the prediction of center coordinates in $\mathbf{f}_1$, the center coordinate of the bee in $\mathbf{f}_0$ is utilized as is, owing to the unavailability of coordinates for the last two points. The predicted BBox $\mathbf{p}_k$ for the bee in the subsequent frame incorporates the width w_{k-1} and height h_{k-1} of the state BBox from the previous frame: $\mathbf{p}_k = (x_k^{\text{pred}}, y_k^{\text{pred}}, w_{k-1}, h_{k-1})$.

2) UPDATE STATE

The bee's state BBox $\mathbf{z}_k = (x_k, y_k, w_k, h_k)$ is determined based on the detected BBox $\mathbf{d}_k$ assigned from IgnitusManager in relation to the predicted BBox $\mathbf{p}_k$. If IgnitusManager assigns $\mathbf{d}_k = (x_k^{\text{detect}}, y_k^{\text{detect}}, w_k^{\text{detect}}, h_k^{\text{detect}})$, the current state BBox is directly updated with $\mathbf{z}_k \leftarrow \mathbf{d}_k$, and τ_{lost} set to 0. In cases where inaccurate bee detection results in no assigned detected BBox from IgnitusManager, IgnitusModel temporarily updates the state BBox using $\mathbf{z}_k \leftarrow \mathbf{p}_k$ and increments τ_{lost} by $\tau_{\text{lost}} + 1$. These temporary updates contribute to reducing ID switches caused by detection results, as compared to conventional bee tracking methods.

3) PURGED UPDATE STATE

When IgnitusManager identifies a detected BBox in a merged situation, it divides this false detection and determines the bee state BBox. In this study, we call this process Purged Update.

Algorithm 1 Pseudo Code of IgnitusTracker. In Contrast to BYTE, IgnitusTracker Facilitates the Utilization of GIoU for Gauging Similarity Between Detections and Predictions, Identifying Merged Situations, and Additionally Supporting the Implementation of Purged Updates Within IgnitusModel.

Input: frame $\mathbf{f}_k$; object detection model Detect; high detection score threshold τ_{high}; low detection score threshold τ_{low};
Output: Deleted IgnitusModels $\mathcal{T}_k^{\text{del}}$;
 # Object Detection
$\mathcal{D}_k \leftarrow$ Detect($\mathbf{f}_k$)
deviding $\mathcal{D}_k$ based on τ_{high} and τ_{low}
$\mathcal{D}_k^{\text{high}} \leftarrow$ high score detections from $\mathcal{D}_k$
$\mathcal{D}_k^{\text{low}} \leftarrow$ low score detections from $\mathcal{D}_k$
 # Location prediction
for t in $\mathcal{T}_{k-1}$ **do**
  $t.prediction()$
end for
 # High Score Detections Matching
Associate $\mathcal{T}_{k-1}$ and $\mathcal{D}_k^{\text{high}}$ using GIoU
$\text{Match}_{\mathcal{D}_k^{\text{high}}, \mathcal{T}_{k-1}} \leftarrow$ *matching pair*
$\text{Merge}_{\mathcal{D}_k^{\text{high}}, \mathcal{T}_{k-1}, \mathcal{T}_{k-1}} \leftarrow$ *merging pair*
$\mathcal{D}_k^{\text{remain}} \leftarrow remainingdetectionsfrom \mathcal{D}_k^{\text{high}}$
$\mathcal{T}_k^{\text{remain}} \leftarrow remainingtracksfrom \mathcal{T}_{k-1}$
for d, t in $\text{Match}_{\mathcal{D}_k^{\text{high}}, \mathcal{T}_{k-1}}$ **do**
  $t.update(d)$
end for
for d, t_1, t_2 in $\text{Merge}_{\mathcal{D}_k^{\text{high}}, \mathcal{T}_{k-1}, \mathcal{T}_{k-1}}$ **do**
  t_1.purged_update(d)
  t_2.purged_update(d)
end for
 # Low Score Detections Matching
Associate $\mathcal{T}_k^{\text{remain}}$ and $\mathcal{D}_k^{\text{low}}$ using GIoU
$\text{Match}_{\mathcal{D}_k^{\text{low}}, \mathcal{T}_k^{\text{remain}}} \leftarrow$ *matching pair*
$\text{Merge}_{\mathcal{D}_k^{\text{low}}, \mathcal{T}_k^{\text{remain}}, \mathcal{T}_k^{\text{remain}}} \leftarrow$ *merging pair*
$\mathcal{T}_k^{\text{re-remain}} \leftarrow remainingtracksfrom \mathcal{T}_k^{\text{remain}}$
for d, t in $\text{Match}_{\mathcal{D}_k^{\text{low}}, \mathcal{T}_k^{\text{remain}}}$ **do**
  $t.update(d)$
end for
for d, t_1, t_2 in $\text{Merge}_{\mathcal{D}_k^{\text{low}}, \mathcal{T}_k^{\text{remain}}, \mathcal{T}_k^{\text{remain}}}$ **do**
  t_1.purged_update(d)
  t_2.purged_update(d)
end for
 # Assign and delete trackers based on conditions
$\mathcal{T}_k^{\text{del}} \leftarrow$ deleting some trackers from $\mathcal{T}_k^{\text{re-remain}}$
$\mathcal{T}_k^{\text{new}} \leftarrow$ assigning new trackers from D_k^{remain}
$\mathcal{T}_k \leftarrow (\mathcal{T}_{k-1} \cup \mathcal{T}_k^{\text{new}}) \setminus \mathcal{T}_k^{\text{del}}$
return $\mathcal{T}_k^{\text{del}}$

The Manhattan distance is initially calculated between the four corners of the predicted BBox $\mathbf{p}_k$ and the detected BBox $\mathbf{d}_k$. The corner of the detected BBox $\mathbf{d}_k$ with the smallest distance is selected among these distances. The state BBox

$\mathbf{z}_k$ is updated by shifting the predicted BBox $\mathbf{p}_k$ to match the corner with this selected corner. In cases of merged situations, the process allows one erroneously detected BBox to be divided into two separate BBoxes, each corresponding to the size of one bee. This facilitates accurate tracking in such scenarios. By incorporating IgnitusManager's BBox score handling process, the Purged Update helps mitigate tracking failures caused by temporary drops in detection scores.

B. IGNITUSMANAGER

During this process, IgnitusManager associates the predicted BBoxes from multiple IgnitusModels with the detected BBoxes through object detection. Similar to BYTE, the scores of the detected BBoxes are utilized in this association process.

1) DATA ASSOCIATION

Detected BBoxes are associated with predicted BBoxes based on the scores of the detected BBoxes obtained through object detection, similar to BYTE. The association process is executed separately for BBoxes with high scores, which likely accurately capture bees, and BBoxes with low scores, which may contain noise or bees with motion blur. Associating them separately according to their scores does not inhibit the association of BBoxes with high scores. Moreover, it realizes the association of low score BBoxes covering bees. IgnitusModel's predicted BBoxes are associated with the BBoxes with high scores τ_{high}, and subsequently, IgnitusModel's predicted BBoxes that were unassociated are associated with the BBoxes with low scores τ_{low}. The association of high and low scores is executed in the same manner. Optimal detected BBox can be assigned to the IgnitusModel's predicted BBox by optimizing using the Hungarian Algorithm [29] based on the similarity between the detected and predicted BBox.

For newly appeared bees, IgnitusModels are created from high score detections that were not associated. When the count of consecutive substitutions τ_{lost} exceeds a threshold, it is considered that the bee has flown off the frame or tracking is lost, leading to the deletion of the corresponding IgnitusModel.

2) SIMILARITY METRIC

During the process of data association, Having the ability to compute distances is crucial for similarity calculations even when the predicted BBox and detected BBox do not overlap due to abrupt changes in the bee's direction of movement. Moreover, it is essential to consider the size and shape of BBoxes in similarity calculations. IoU is represented by (Equation 2) when dealing with two BBoxes, A and B, and it results in all zeros if the predicted BBoxes do not overlap.

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

Therefore, we use GIoU (Equation 3) [20], [30], which considers the smallest convex shape C enclosing A and B, to calculate the distance, size, and, shape between the BBoxes appropriately.

$$\text{GIoU} = \text{IoU} - \frac{|C \setminus (A \cup B)|}{|C|} \tag{3}$$

Because GIoU is scale-invariant, it allows for the assessment of similarity between the predicted and detected BBoxes regardless of the distance between the camera and the bee. As a result, IgnitusManager can utilize this property to pass the most similar detection results to IgnitusModel, aligning with the behavioral characteristics of the bees.

3) DETERMINING MERGED SITUATION

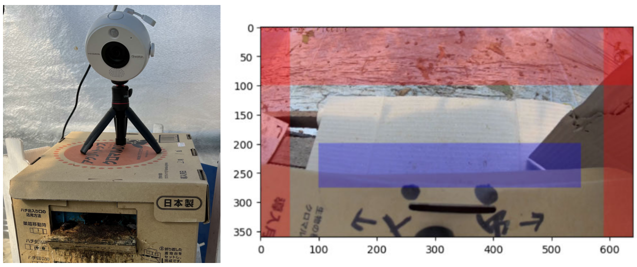
Post data association, the merged situation is identified by determining whether two predicted BBoxes from different IgnitusModels simultaneously overlap with a single detected BBox. Such an overlap scenario results in one predicted BBox being associated while the other is not. If an IoU $>$ 0 exists between an unassociated predicted BBox and an associated detected BBox, it signifies the presence of another predicted BBox associated with the same detected BBox. Recognizing this scenario as a merged situation, these two IgnitusModels execute a purge update. When a merged situation involving three or more bees occurs, three or more predicted BBoxes compete for a single detected BBox, in which case the purge update is performed on the pair with the largest IoU between the associated and unassociated predicted BBoxes.

IV. EXPERIMENTS

To assess the effectiveness of IgnitusTracker in tracking *B. ignitus* and accurately counting their arrivals and departures to and from the hive, we conducted a comparative analysis with existing methods. Specifically, for accuracy comparison, we employed SORT [28] and BYTE [21] for pedestrian and vehicle tracking, while Yang and Collins (Y&C) [9] tracking method was used for honeybees. These three existing methods were used because, compared to IgnitusTracker's processing, BYTE has a score-based associating process, Y&C has a process for decomposing erroneously detected BBox containing two bees, and SORT has neither. In addition, to validate IgnitusTracker's performance in a real-world scenario, we installed devices equipped with IgnitusTracker on an actual farm. This allowed us to tally the arrivals and departures of *B. ignitus* workers and males from when the hive was set up by the farmer until it was replaced.

A. IMPLEMENTATION

In the context of a farm where *B. ignitus* were engaged in crop pollination, a camera (IO-DATA TS-NS410W [31], 1920 × 1080 pixels, 30 FPS) was deployed. The camera was positioned approximately 15 cm above a hive designed for *B. ignitus* (Agrisect Inc.'s hive [32]), ensuring that both the *B. ignitus* (Fig. 2 (a)) and the hive entrance/exit were within its field of view (Fig. 2 (b)). A camera was installed in each of the two hives set up by the farmer in the field to capture video



(a) (b)

FIGURE 2. A camera installed on a hive and its field of view. (a) A camera placed on top of a *B. ignitus* hive was fixed on a tripod at a height of about 15 cm from the hive. (b) Predefined inside and outside areas in the video. The inside area, denoted by the blue region, signifies the hive entrance, while the outside area, represented by the red region, designates a considerable distance from the hive.

footage of *B. ignitus*. Given their heightened activity during daylight hours, the recording was conducted between March 2023 to May 2023, between 9:00 a.m. and 4:00 p.m.. The recorded camera footage was processed on an edge device (NVIDIA's Jetson AGX Orin [33]) to calculate the count of *B. ignitus* arrivals and departures (Fig. 3).

We employed YOLOv5 [34] as the deep learning model for object detection. For computational efficiency on edge devices, we used images resized from 1920×1080 pixels to 640×360 pixels as input to YOLOv5. YOLOv5 was trained on 792 images containing *B. ignitus* males and workers, with their BBoxes annotated respectively.

Five test datasets (V1-V5) were created to evaluate the accuracy and computational efficiency of the IgnitusTracker. These five test datasets consisted of different time periods on different dates to ensure accurate evaluation in diverse environments. Each test data is about a 20-second video extracted from several videos by removing continuous frames where bees do not appear for long periods of time to shorten the computation time on the edge devices. We manually annotated a total of 3418 frames across the five test datasets. The ground truth of the number of bees arriving at and departing from the hives was based on the ground truth of the bee tracking. LabelImg [35] was used as the annotation tool. In scenarios where a bee exited the camera's field of view and subsequently re-entered, we considered it a new bee rather than assuming continuity. Regarding the hyperparameters of IgnitusTracker, we determined the threshold values for GIoU, τ_{lost}, τ_{high}, and τ_{low} through trial and error with the captured video footage. The set threshold values were -0.75 for GIoU, 3 for τ_{lost}, 0.5 for τ_{high}, and 0.1 for τ_{low}.

B. JUDGING BEE ARRIVAL AND DEPARTURE BASED ON TRACKING RESULTS

Upon bees' arrival at the hive, those that emerged from beyond the frame become concealed beneath the hive entrance. Conversely, when bees departed from the hive, those initially visible at the entrance vanished beyond the frame's boundary. By integrating this characteristic into the arrival/departure decision framework, we determined instances of arrival and departure using the tracking outcomes.

In the initial stages, we delineated two specific areas within the frame to establish criteria for identifying the entry and exit of bees in the video footage. These two designated areas comprise the following: The first, an inside area, defined as the zone where a bee is considered to have entered the hive, even if it becomes unobservable within the frame. The second, an outside area, defined as the region in which a bee is deemed to have exited the camera's field of view, despite its disappearance from the frame. (see Fig. 2b for a visual representation). The specification of these areas was carried out through a careful analysis of both the recorded footage from the installed cameras and the observed behaviors of the bees.

Determining whether a bee belongs to these areas hinges on whether the central coordinates of the bee fall within the specified regions. Within a single bee tracking result, we establish the following definitions: If a bee is initially observed within the inside area but is last seen within the outside area, we classify this sequence as a "Departure". Conversely, if a bee is initially spotted in the outside area and concludes its observation within the inside area, we label it as an "Arrival" (Fig. 4). This assessment occurs during removing the IgnitusModel, as outlined in Algorithm 2. The algorithm processes the tracking results recorded by the IgnitusModel to make the arrival and departure determinations. The tracking and recording of bee arrivals and departures is accomplished through the persistent application of this judgment process over an extended period. Notice that this is not the method, but the problem setting.

C. MEASURES

For the assessment of whether object detection accurately identified the bounding boxes (BBoxes) of male and worker bees, we employed the mean Average Precision (mAP@0.5) metric. Additionally, the processing speed of the object detection was evaluated in terms of the frame rate. Uniform output from YOLOv5 was utilized as input across all tracking methods. To evaluate the accuracy of IgnitusTracker, we adopted the evaluation approach of BYTE [21]. This involved metrics such as MOTA [36], IDF1 [37], ID Switch (IDs), and the frame rate. Among these indices, MOTA focuses on detection accuracy, IDF1 focuses on association performance, and IDs indicate instances where the assigned ID for an entity has changed. Considering that the tracking pertains to both worker and male bees in the case of the *B. ignitus* study, we employed metrics such as mMOTA, mIDF1, and mIDs, averaging evaluations across the entire class. Since arrival and departure determinations are drawn from the tracking results based on assigned IDs for the bees, larger values of IDs exert a significant influence on accuracy. Therefore, methods with lower IDs and substantial MOTA and IDF1 scores are particularly crucial within the context

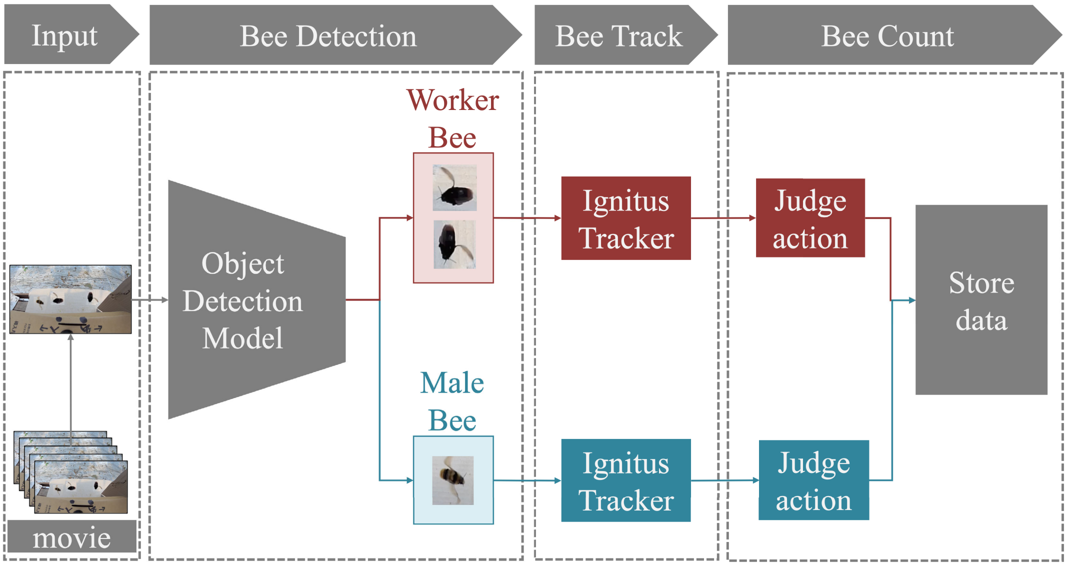


FIGURE 3. **Procedure for counting the arrivals and departures of *B. ignitus* from videos taken from the top of the hive. After the bees are detected, they are tracked, and their arrival and departure are judged and counted.**

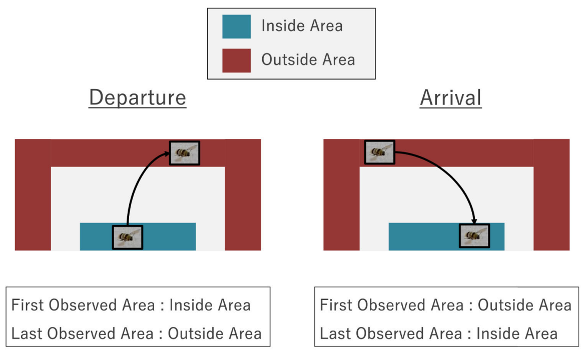


FIGURE 4. **Based on the trajectory of the bee's center coordinates recorded by IgnitusModel, if the first observed area is the inside area and the last observed area is the outside area, then it is defined as a departure; if the first observed area is the outside area and the last observed area is the inside area, then it is defined as an arrival.**

of this study. For assessing the count of bees arriving at and departing from the hive, we employed the Mean Absolute Error (MAE), representing the absolute discrepancy between the actual and predicted counts of departures and arrivals. This evaluation was averaged across the various classes.

V. RESULTS

A. BEE DETECTION

The outcomes regarding the detection accuracy of YOLOv5, employed for object detection, are presented in Table. 1. These detection results were subsequently utilized to assess the performance of the tracking methods.

B. BEE TRACKING

A summarized representation of the tracking accuracy results for *B. ignitus* is available in Table. 2. Based on the MOTA metric, IgnitusTracker demonstrated accuracy on par with the Y&C tracking method. However, considering IDF1 and IDs metrics, IgnitusTracker exhibited superior accuracy. Notably, the IDs metric reflected an improvement of more

Algorithm 2 Pseudo Code of Judging Whether Bee Arrivals or Departures. AreaChecker Returns 0 If the Area Containing the Center Coordinates of the Bee Is Inside Area and 1 If It Is Outside Area.

Input: frame $\mathbf{f}_k$; video $\mathcal{V}$; Object detection model Detect; object tracking Track;
Output: count of arrival N_a, count of departure N_d;

Initialisation : $N_a, N_d = 0, 0$
for $\mathbf{f}_k$ in $\mathcal{V}$ **do**
  # Object Detection
  $\mathcal{D}_k \leftarrow \text{Detect}(\mathbf{f}_k)$
  # Object Tracking
  $\mathcal{T}_k^{\text{del}} \leftarrow \text{Track}(\mathcal{D}_k)$
  # Judeging Arrival and Departure
  for t in $\mathcal{T}_k^{\text{del}}$ **do**
    # First Observed Area
    $i \leftarrow \text{AreaChecker}(t.\text{first})$
    # Last Observed Area
    $j \leftarrow \text{AreaChecker}(t.\text{last})$
    if $(i == 1)$ & $(j == 0)$ **then**
      N_a += 1
    else if $(i == 0)$ & $(j == 1)$ **then**
      N_d += 1
    end if
  end for
end for

TABLE 1. The test data (V1-V5) was used to evaluate tracking. hive1 and hive2 indicate the respective hive, am/pm indicates the time of day, N_w and N_m indicate the total number of worker and male bee tracking IDs, and F_w and F_m indicate the number of frames in which workers and males appear.

Video	Description							YOLOv5	
	Frames	N_w	N_m	F_w	F_m	Hive	AM/PM	mAP@0.5	FPS
V1	618	7	11	239	259	hive1	pm	91.3	43.9
V2	865	27	4	470	115	hive1	pm	89.7	44.6
V3	639	16	6	479	206	hive2	pm	81.7	43.1
V4	643	15	0	222	0	hive1	am	94.9	47.0
V5	653	20	1	425	28	hive2	am	88.6	40.9

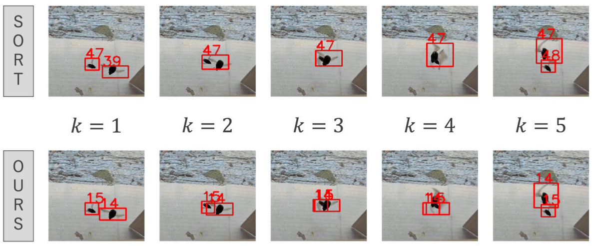


FIGURE 5. An example under a merged situation. k is the temporal order of the frames. The number on the upper left corner of the red BBox indicates the ID assigned to the bee. The upper set of five frames shows the results from SORT, which follows the detection results directly and has no processing for the BBox. The lower set of five frames shows the results from IgnitusTracker, which performs processing based on BBox scores (BYTE) and purge updates (Y&C).

than 50% compared to existing methods. Regarding frame rate, IgnitusTracker ranked as the second-best among all the comparative tracking methods. Moreover, as illustrated in Fig. 5, the utilization of IgnitusTracker allowed for the tracking of individual bees even within merged situations.

C. BEE COUNT IN ARRIVALS AND DEPARTURES

The outcomes pertaining to the accuracy of arrival and departure counting for each tracking method are presented in Table. 3. Notably, IgnitusTracker consistently exhibited smaller errors in the count of arrivals and departures across all test datasets compared to the other tracking methods.

The time-series changes in the counts of arrivals and departures for *B. ignitus* males and workers, as recorded using IgnitusTracker, are visually represented in Fig. 6. The hive featured in the video was set up on March 30, 2023, and subsequently replaced on May 13, 2023, based on the farmer's judgment. While the farmers were unaware of the arrival and departure counts tracked using IgnitusTracker, an observable trend emerged within this hive. As the replacement date, determined by the farmers, drew closer, there was a reduction in the number of worker bee arrivals and departures, accompanied by an increasing trend in male bee arrivals and departures. Interestingly, despite the fact that male bees typically increase in number as their life cycle nears its end, we noted a higher count of male bee arrivals and departures right from the installation date.

VI. DISCUSSION

Combining simple components, IgnitusTracker can track bees with high computational efficiency and accuracy even on

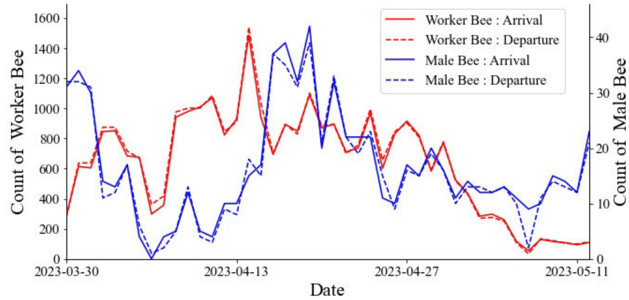


FIGURE 6. Trends in the number of worker and male bees arriving and departing by date from March 30, 2023, to May 13, 2023. The red line indicates worker bees, the blue line indicates male bees, the solid line indicates arrivals, and the dashed line indicates departures. The left axis shows the number of worker arrivals and departures, and the right axis shows the number of male arrivals and departures.

edge devices with limited computation resources. The results presented in Table 3 strongly suggest that IgnitusTracker significantly enhances the accuracy of counting *B. ignitus* arrivals and departures. The noteworthy improvement in IgnitusTracker's mIDF, compared to the tracking method by Y&C, can be attributed to GIoU's consideration of the size and shape between BBoxes during association. The reduced mIDs of IgnitusTracker could stem from its handling of false detections by incorporating the BBox score within merged situations. Although IgnitusTracker exhibited a lower FPS than Y&C, this is likely due to IgnitusTracker performing association twice by splitting processes based on BBox scores, in contrast to Y&C. Conversely, IgnitusTracker's relatively high FPS, despite performing more operations than SORT and BYTE, can be attributed to the greater computational efficiency of IgnitusModel over Kalman Filter. However, the object detection method used in this study (YOLOv5) has a much lower FPS than the tracking methods. Consequently, the frame rate of object tracking is unlikely to impact the overall processing time significantly. A limitation of IgnitusTracker is that it does not support merged situations in which more than three bees cross. However, since there were few cases in which three bees crossed simultaneously, we don't consider that this has a significant impact on tracking accuracy. Our test data contained the video with a small number of male bees. Male bees as many as worker bees could not be observed over time, which might be caused by lifestyle differences. However, the effect on the accuracy and computational efficiency was considered small because both male and worker bees in the video acted similarly.

Employing Ignitus Tracker to count the arrivals and departures of *B. ignitus* males and workers enabled us to capture a segment of the species' life cycle. This revealed a decline in worker bees and an increase in male bees, which are characteristic trends towards the end of their life cycle. Therefore, it is foreseeable that determining the appropriate time for hive replacement can be refined based on the counted arrivals and departures of bees within the hive. The prevalence of male arrivals and departures, even from the initial date of hive installation, could potentially be elucidated

TABLE 2. Comparison between proposed and existing methods in tracking accuracy of *B. ignitus*. SORT represents the method of Bewley et al. [28], BYTE represents the method of Zhang et al. [21], and Y&C represents Yang and Collins [9] method, and OURS represents IgnitusTracker.

Video	mMOTA				mIDF1				mIDs				FPS			
	SORT	BYTE	Y&C [9]	OURS	SORT	BYTE	Y&C [9]	OURS	SORT	BYTE	Y&C [9]	OURS	SORT	BYTE	Y&C [9]	OURS
V1	60.3	59.7	84.6	**85.2**	68.9	68.8	86.2	**91.5**	5.0	5.0	1.5	**0.5**	5395.7	4825.4	**10196.4**	7220.3
V2	48.3	48.1	**73.9**	73.8	64.1	63.9	**87.5**	**87.5**	12.0	12.0	1.0	**0.5**	6065.8	5260.2	**11409.1**	7705.0
V3	45.5	46.9	69.6	**70.6**	52.7	53.5	73.7	**77.3**	22.0	20.0	10.5	**3.5**	3836.8	3381.4	**7447.5**	5304.8
V4	81.4	81.4	91.9	**92.3**	86.0	86.0	93.3	**93.6**	10.0	10.0	**1.0**	**1.0**	10309.7	8479.0	**17829.9**	10873.2
V5	30.3	28.3	**75.1**	73.1	52.7	52.5	84.7	**87.0**	7.5	7.5	4.0	**1.5**	5815.2	5073.3	**10169.8**	6865.4
Average	53.2	52.9	**79.0**	**79.0**	64.9	64.9	85.1	**87.4**	11.3	10.9	3.6	**1.4**	6284.6	5403.9	**11410.5**	7593.7

TABLE 3. MSE of arrival and departure determined by each tracking method.

Video	Departure				Arrival			
	SORT	BYTE	Y&C [9]	OURS	SORT	BYTE	Y&C [9]	OURS
V1	1.0	1.0	0.5	**0.0**	**0.5**	**0.5**	1.0	**0.5**
V2	1.0	1.0	**0.0**	**0.0**	1.5	1.5	**0.0**	**0.0**
V3	1.5	1.5	1.0	**0.5**	0.5	1.0	0.5	**0.0**
V4	1.0	1.0	**0.0**	**0.0**	1.0	1.0	**0.0**	**0.0**
V5	1.0	**0.0**	1.5	**0.0**	1.0	1.0	1.0	**0.0**
Average	1.1	0.9	0.6	**0.1**	0.9	1.0	0.5	**0.1**

by considering the activity of male bees in the older hive with the almost end of the life cycle that was set up before the current hive.

VII. FUTURE WORK

This study focused on bee activity spanning seven hours, from 9:00 a.m. to 4:00 p.m. However, *B. ignitus* exhibits activity in the early morning hours. Consequently, determining whether restricting analysis to this time frame adequately captures the activity trends of worker and male bees presents a challenge, warranting further investigation.

In this research, we introduced IgnitusModel as a replacement for Kalman Filter, incorporated GIoU instead of IoU or pixel distance, and devised a mechanism for score-aware false detection handling. Regarding the use of IgnitusModel, further investigation is necessary to determine the essential components that contribute to accurate counting.

VIII. CONCLUSION

In this study, we proposed IgnitusTracker, a novel method designed for tracking *B. ignitus* males and workers using video footage captured on a farm. IgnitusTracker demonstrated higher tracking precision and accuracy in quantifying arrivals and departures compared to existing methods. Results from IgnitusTracker's counts of bee arrivals and departures within the hive revealed a notable trend: as the designated time for hive replacement approached, the number of worker bees decreased, while the count of male bees increased. Therefore, it is expected that utilizing IgnitusTracker's counts of bee arrivals and departures can assist in determining the optimal timing for hive replacement.

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REFERENCES

[1] H. J. Yoon and I. G. Park. (Jul. 2019). *Current Status and Agricultural Utilization of Insect Pollinators in Korea*. [Online]. Available: https://www.niaes.affrc.go.jp/sinfo/sympo/h22/1109/paper_

[2] S. Mohamadzade Namin, J. Huang, J. An, and C. Jung, "Genetic variation and phylogenetic relationships of commercial populations of bombus ignitus (hymenoptera, Apidae) with wild populations in eastern Asia," *J. Hymenoptera Res.*, vol. 96, pp. 495–506, Jun. 2023.

[3] T. Han, H. Park, I. G. Park, H. J. Yoon, K. Kim, and H. J. Lee, "Genetic structure of Korean populations of bumblebees bombus ignitus (hymenoptera: Apidae) as revealed by microsatellite markers," *Entomological Res.*, vol. 44, no. 6, pp. 262–270, Nov. 2014.

[4] Ministry of the Environment. *Bombus Terrestris*. Accessed: May 9, 2023. [Online]. Available: https://www.env.go.jp/nature/intro/2outline/attention/seiyou.html

[5] Forestry Ministry of Agriculture and Fisheries. *About Pollinator Insects*. Accessed: May 9, 2023. [Online]. Available: https://www.maff.go.jp/j/chikusan/gijutu/mitubati/

[6] National Institute of Environmental Studies. *Research on Ecological Risk Assessment and Countermeasures for the Bombus Terrestris*. Accessed: May 9, 2023. [Online]. Available: https://www.nies.go.jp/biodiversity/invasive/project1.html

[7] P. Nunes-Silva, M. Hrncir, J. T. F. Guimarães, H. M. Arruda, L. Costa, G. Pessin, J. O. Siqueira, P. de Souza, and V. L. I. Fonseca, "Applications of RFID technology on the study of bees," *Insectes sociaux*, vol. 66, pp. 15–24, Sep. 2019.

[8] D. Heise, Z. Miller, E. Harrison, A. Gradišek, J. Grad, and C. Galen, "Acoustically tracking the comings and goings of bumblebees," in *Proc. IEEE Sensors Appl. Symp. (SAS)*, Mar. 2019, pp. 1–6.

[9] C. Yang and J. Collins, "A model for honey bee tracking on 2D video," in *Proc. Int. Conf. Image Vis. Comput. New Zealand (IVCNZ)*, Nov. 2015, pp. 1–6.

[10] A. Shaout and N. Schmidt, "Bee hive monitor," in *Proc. Int. Arab Conf. Inf. Technol. (ACIT)*, Dec. 2019, pp. 52–57.

[11] M. N. Ratnayake, A. G. Dyer, and A. Dorin, "Tracking individual honeybees among wildflower clusters with computer vision-facilitated pollinator monitoring," *PLoS ONE*, vol. 16, no. 2, Feb. 2021, Art. no. e0239504.

[12] B. Magnier, G. Ekszterowicz, J. Laurent, M. Rival, and F. Pfister, "Bee hive traffic monitoring by tracking bee flight paths," in *Proc. 13th Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl.*, Funchal, Madeira, Portugal, 2018, pp. 563–571.

[13] M. Nisal Ratnayake, A. G. Dyer, and A. Dorin, "Towards computer vision and deep learning facilitated pollination monitoring for agriculture," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2021, pp. 2915–2924.

[14] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 28, 2015, pp. 1–12.

[15] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2980–2988.

[16] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," 2020, *arXiv:2004.10934*.

[17] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, "YOLOX: Exceeding YOLO series in 2021," 2021, *arXiv:2107.08430*.

[18] G. Welch and G. Bishop, "An introduction to the Kalman filter," Dept. Comput. Sci. Univ. North Carolina Chapel Hill, Chapel Hill, NC, USA, Tech. Rep. TR 95-041, 1995.

[19] N. Wojke, A. Bewley, and D. Paulus, "Simple online and realtime tracking with a deep association metric," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2017, pp. 3645–3649.
[20] Y. Wang, D. Huang, Y. Shi, L. Chen, and L. Chen, "Online multi-object tracking with generalized IoU gating mechanism," in *Proc. China Autom. Congr. (CAC)*, Nov. 2022, pp. 3943–3947.
[21] Y. Zhang, P. Sun, Y. Jiang, D. Yu, F. Weng, Z. Yuan, P. Luo, W. Liu, and X. Wang, "Bytetrack: Multi-object tracking by associating every detection box," in *Proc. Comput. Vis. ECCV 17th Eur. Conf.*, Tel Aviv, Israel. Cham, Switzerland: Springer, Oct. 2022, pp. 1–21.
[22] Y. Du, Z. Zhao, Y. Song, Y. Zhao, F. Su, T. Gong, and H. Meng, "StrongSORT: Make DeepSORT great again," *IEEE Trans. Multimedia*, vol. 25, pp. 8725-8737, 2023, doi: 10.1109/TMM.2023.3240881.
[23] Y. Zhang, C. Wang, X. Wang, W. Zeng, and W. Liu, "FairMOT: On the fairness of detection and re-identification in multiple object tracking," *Int. J. Comput. Vis.*, vol. 129, no. 11, pp. 3069–3087, Nov. 2021.
[24] F. Gu, J. Lu, C. Cai, Q. Zhu, and Z. Ju, "EANTrack: An efficient attention network for visual tracking," *IEEE Trans. Autom. Sci. Eng.*, vol. 99, pp. 1–18, 2023.
[25] F. Gu, J. Lu, C. Cai, Q. Zhu, and Z. Ju, "Repformer: A robust shared-encoder dual-pipeline transformer for visual tracking," *Neural Comput. Appl.*, vol. 35, no. 28, pp. 20581–20603, Oct. 2023.
[26] V.-H. Tran, L.-H.-H. Dang, C.-N. Nguyen, N.-H.-L. Le, K.-P. Bui, L.-T. Dam, Q.-T. Le, and D.-H. Huynh, "Real-time and robust system for counting movement-specific vehicle at crowded intersections," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2021, pp. 4223–4230.
[27] A. Dirir, M. Adib, A. Mahmoud, M. Al-Gunaid, and H. El-Sayed, "An efficient multi-object tracking and counting framework using video streaming in urban vehicular environments," in *Proc. Int. Conf. Commun., Signal Process., Appl. (ICCSPA)*, Mar. 2021, pp. 1–7.
[28] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft, "Simple online and realtime tracking," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2016, pp. 3464–3468.
[29] H. W. Kuhn, "The Hungarian method for the assignment problem," *Nav. Res. Logistics (NRL)*, vol. 52, no. 1, pp. 7–21, Feb. 2005.
[30] H. Rezatofighi, N. Tsoi, J. Gwak, A. Sadeghian, I. Reid, and S. Savarese, "Generalized intersection over union: A metric and a loss for bounding box regression," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 658–666.
[31] IO DATA. *Network Camera Ts-ns410w*. Accessed: Jun. 12, 2023. [Online]. Available: https://www.iodata.jp/product/lancam/lancam/ts-ns410w/
[32] Agrisect Inc. (2023). *Agri-top Kuromaru Dx*. [Online]. Available: https://www.agrisect.com/80337.html
[33] NVIDIA Corporation. *Jetson Agx Orin for Next-Gen Robotics*. Accessed: Jun. 12, 2023. [Online]. Available: https://www.nvidia.com/en-il/autonomous-machines/embedded-systems/jetson-orin/
[34] G. Jocher, "YOLOv5 by ultralytics," Tech. Rep., May 2020. [Online]. Available: https://github.com/ultralytics/yolov5
[35] Tzutalin, "Labelimg," Tech. Rep., 2015. [Online]. Available: https://github.com/HumanSignal/labelImg
[36] K. Bernardin and R. Stiefelhagen, "Evaluating multiple object tracking performance: The CLEAR MOT metrics," *EURASIP J. Image Video Process.*, vol. 2008, pp. 1–10, 2008.
[37] E. Ristani, F. Solera, R. Zou, R. Cucchiara, and C. Tomasi, "Performance measures and a data set for multi-target, multi-camera tracking," in *Proc. Eur. Conf. Comput. Vis.* Cham, Switzerland: Springer, 2016, pp. 17–35.

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