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AntTracker: A low-cost and efficient computer vision approach to research leaf-cutter ants behavior

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ABSTRACT

Leaf-cutter ants play a crucial role in agroecosystems, and understanding their behavior is key to developing effective damage control strategies. While several tracking solutions exist for ants in controlled environments or on aerial images, accurately measuring ant behavior in the wild remains a challenge. In this work, we propose a three-stage processing pipeline that segments individual ants, tracks their movement, and classifies whether they are carrying a leaf using a convolutional neural network. The output of the pipeline includes a timestamped record of the activity on the trail, accounting for parameters such as ant velocity, size and if it is going from or to the nest. We use the recently developed portable device AntVideoRecord to register video of a selected ant trail. To validate our approach, we collected a labeled dataset and evaluated each stage using standard metrics, achieving a median F2 score of 83% for segmentation, MOTA of 97% for tracking and F1 of 82% for detecting ants carrying a leaf. We then carried out a larger use case in the wild, demonstrating the effectiveness of our approach in capturing the intricate behaviors of leaf-cutter ants. We believe our method has the potential to inform the development of more effective ant damage control strategies in agroecosystems.

1. Introduction

Leafcutter ants (LCA) are known for their activity of cutting various plant fragments, being destructive pests in the neotropical region [1–5] mainly to cultivate fungi. They play an important role as 'ecosystem engineers' since they modify its structure and function [6–8]. Their foraging capacity is the main activity that arouses the greatest interest in study due to its effects on agroecosystems. They are capable of using between 50 and 80% of the available plant species from various plant communities [9]. *Atta* and *Acromyrmex* are the most important LCA genera that obtain their food from short to long distances due to the size of the workers and consequently the size of the nest. Forage activity is affected by biotic and abiotic factors [10–12]. Also, Activity rhythms of LCA based on endogenous factors such as photoperiod and annual thermal cycle have recently been studied [13].

In South America, LCA forage 15% per year of tropical forest vegetation [9] and about 50% of them are herbaceous species [14]. Estimates have determined that a nest can cut, carry and process between 20 to 1000 kg of plant material per year in the form of millions of bits of leaves and flowers [15]. Not only do they cut large amounts of vegetation in natural ecosystems, but also anthropic ecosystems are affected, causing significant economic damage to forest crops (eg Pinus spp., Eucalyptus spp.), agricultural crops (eg *Citrus* spp., *Theobroma cacao, Manihot esculenta, Coffea arabica, Zea mays, Gossypium hirsutum*) and in natural grasslands or implanted pastures where extensive livestock is developed [16–18]. All the estimates mentioned arise from discrete evaluations over time and recorded in brief times during the day, rarely 24 h.

Methods for estimating yield losses by leaf-cutting ants vary according to the agricultural system. The simplest assessments occur in forestry and agriculture immediately after planting, where losses are easily estimated by counting losses of seedlings. On the other hand, losses in adult agricultural and forestry plantations and cattle husbandry are more difficult. In this case ant consumption can be estimated by two methods. First, in the exclusion method ants are precluded from cutting the plants of interest. It is performed by killing the colonies, or by avoiding ants reaching the plants using exclusion cages. Second, the herbivory rate method, where all fragments ants cut and carry into the nest are collected for a given period of time, and then the total daily

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consumption is extrapolated. The former suffers from the fact that it also excludes other herbivores and the impossibility of excluding all foraging areas of the colony. The main issue related to the herbivory rate method relies on the impossibility of collecting all fragments carried out by ants. This problem could be easily solved with an autonomous non-human system that counts the ants and the loads they carry around the 24 h of the day.

Machine learning approaches have already been used in several agroindustrial applications [19,20], animal habitat [21] and environmental studies [22]. Insects monitoring is a very time-consuming task, requiring large amounts of trained staff hours and equipment. Here, computer vision approaches showed promising results for several agricultural applications. In [23] an object detection approach was proposed for monitoring Drosophila. They estimate the insect population using traps placed near the crops. From the pictures of such traps, a convolutional neural network (CNN) is trained to detect insect positions and classes for each picture. In [24] Aphids are detected and classified automatically from petri dish photos using an hybrid approach of image processing and deep learning. Moreover, measuring ant activity in a general scale was proposed by estimating nests density from satellite images [25].

An additional layer of complexity is tracking the individual behavior of the insects [26], which is an interesting topic in both biology and computational models [27,28]. There exist several successful tools to track insects [29,30]. More recently, in [31] they propose a device, illumination system and object detectors based on CNN to identify ants in a clear background. In this case, ants are tracked with a codebar attached to their bodies. In [32] they also address the high amount of contact of ants using color tags. All these tools are very precise and useful in specific laboratory settings, but it is not feasible to track behavior on-the-wild.

In order to track insects in natural settings, other approaches are required. In the case of ants, it is still very challenging, as they have chaotic trajectories, colliding with each other very often [33]. Moreover, the ants have mostly the same appearance in video, making it harder to track unique individuals. Modern ant counting studies use conventional video cameras and then manually analyze the videos in slow motion by visually counting the activity, or eventually using the few freely available software available so far. AntCounter is a free access system that counts the number of ants that walk through the center of the video frame (Bustamante and Amarillo-Suárez, 2016). Still, illumination changes and shadows make a huge impact on image processing tasks, where high user intervention is usually required. Moreover, counting can easily get overestimated by errors in the tracking algorithm, in which an erratic ant can be counted as different ants crossing through the checkpoint. Improving the tracking of this kind of behavior automatically would be an important improvement to the behavior science of ants.

In [34] an online ant tracking system is proposed. This system uses a Residual CNN (ResNet) to learn embedding representations (this is, a feature vector) of each ant. They combine similarity metrics and motion metrics using a Kalman filter to identify each ant between frames. The system was built for short videos of less than 30 s. Still, the issue of ant detection (this is, finding the ants in the image) was found to be critical to obtain a good tracking result, and it was not solved yet. Identification using a combination of Fast-masked-RCNN and a tracking system was proposed in [33], where the indoors performance is good, but it drastically drops with outdoor and unseen natural videos. This low performance in detection, according to the authors, makes it unaffordable to run tracking predictions. Others such as [35] use a precise approach with detection using maskRCNN and tracking with optimal transport. However, this requires very high quality videos. On the other hand, low-cost tracking implemented to track bees showed promising results [36].

The labeling process is one of the most time demanding tasks in new computer vision tasks, especially when the application is very narrow and specific as in this case. Several efforts have been made to collect and label ant behavioral data [34,37]. Still important user intervention is required to select the ants with proper bounding boxes. Moreover, in this work we focus on the detection of ants following a path to (and from) their nest with the aim of detecting the number of ants which carry a load, usually a fragment of leaf or grass, to the nest. Given the naturalistic setting of the image acquisition, detecting the load, and linking the ant with the load, is not a trivial task. Leaves can have different shapes and colors, and they are hard to distinguish in one frame alone, especially at night.

In this work we propose a low-cost and effective approach to register and analyze the locomotion and foraging ant activity directly from videos. Unlike the previous works, we propose a solution of ant segmentation and tracking that is robust and can be rapidly improved with assisted tagging, allowing the processing of several hours of video with cheap resolution. To this end, several fronts have to be resolved: limitations of hardware autonomy, background removal, ant segmentation, ant tracking, identification of loaded ants and finally an activity summary per timestamp.

Recently we have found an effective way to register locomotion rhythms continuously in time by means of the AntVRecord [38], an open hardware device that stores video on physical media that must then be analyzed to determine the daily, monthly, or seasonal rate of locomotion and foraging of an LCA nest. Using this hardware, we can record several hours of activity with total autonomy. The device is placed on an ant trail near the nest. This can be seen as a checkpoint where we can measure how many ants go in or out the nest, and extract information about their load and behavior.

In order to process the recorded videos, the proposed pipeline is described in Fig. 1. The first step is to separate the ants from the background, which is not a trivial task in the wild, even with the aid of an uniform background. Using a mixture of gaussians models it is possible to separate background from foreground using spatial and temporal information, making it robust to different recording conditions and with low computational cost. At this point, each pixel in the video is either background or "ant". Then, each ant on a frame can be isolated with precision, associating each ant pixel to a particular ant. If two ants are too close there is a risk of instance segmentation confusion, which is solved with a watershed based algorithm, combined with tracking information from previous frames. The tracking algorithm, based on a Kalman filter, is used to predict the following frame displacement of each identified ant from the current frame. This way, each ant receives an unique id. This is important to count precisely how many ants go from and to the nest, and also to obtain relevant features of the track of each ant, such as their average walking speed and size. Finally, a multi-instance classifier approach was designed to detect if each ant is carrying load. To the best of our knowledge there are no tools to estimate the amount of loaded ants, which is important to estimate their foraging rate. The outcome of the proposed system is a timestamp table with each ant going through the trail checkpoint, detailing their direction (to and from the nest), average size and walking speed, and if it is loaded or not. Moreover, the generated masks (this is, the pixels that represent each ant in each frame) can be easily available for additional analysis or corrections by the user.

The software used for labeling the ants (AntLabeler) uses the same image processing pipeline in an assisted (semi-automatic) way. Basic background removal and segmentation is performed automatically, then the user can correct the masks and edit the tags on each frame using near frame predictions as baseline. This tool will allow us to build a larger dataset in the future to further improve the computer vision methods.

The next section describes in detail the proposed methods. Section 3 describes the process of data collection and curation, and how the performance is measured. Section 4 shows the results obtained on realistic experimental conditions. Finally, important conclusions are drawn in Section 5.

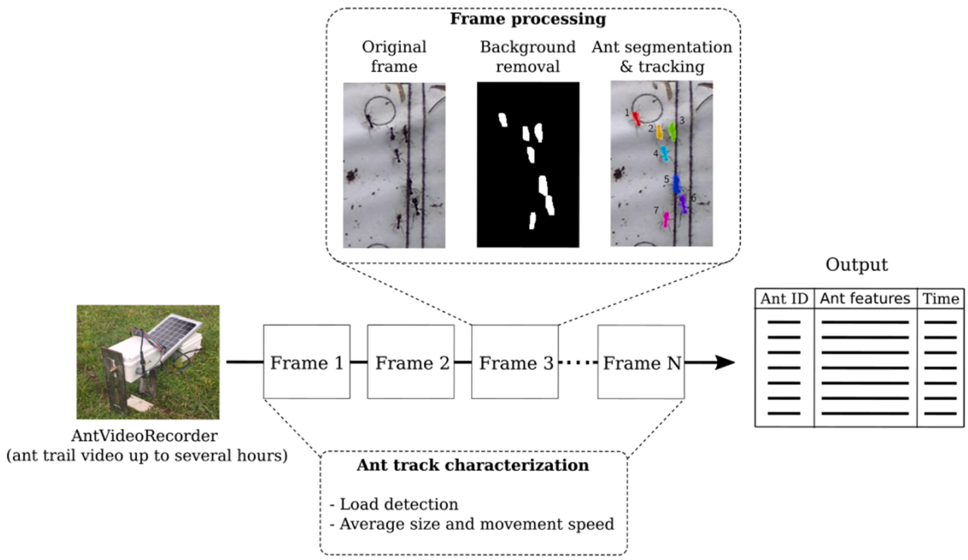

Fig. 1. Proposed ant tracker pipeline. AntVideoRecorder provides continuous videos (up to several hours). A frame-by-frame processing is performed to remove the background and segment each ant. The ants are tracked using current and previous frames, this way each ant is identified as an unique trajectory. Then, information from the trajectory on all the frames is used to determine if the ant is loaded, its direction (from or to the nest) and other features such as average speed and size. The results are exported as a timestamp table.

2. Methods

2.1. Background removal and segmentation

Three well known alternatives for background removal were evaluated: temporal median, mixture of gaussians (MoG) and the GSOC background extractor (Quian 2017). These methods use a series of frames to detect stationary objects which will be tagged as background. With the background mask, a series of morphological operations (closing, opening and hole filling) are applied to eliminate spurious detections and obtain closed regions that completely contain each ant. A structured element of the size of the minimum detectable ant is used. To avoid camera movement and illumination variations, frames where the detected motion is too high will be ignored. This is feasible because the object tracking algorithm (detailed in the next section) can deal with missing data on a frame-by-frame basis.

The Laplacian of Gaussian filter [39] is a basic region detection algorithm. By convolving the image with a gaussian kernel (1), the resulting image contains high intensities in the center of each defined region (each ant), making it possible to separate overlapping regions. A threshold T is computed using (2) to get a binary blob mask per ant, where I<=T is the intensity average below T, and I>T is the intensity average above.

$$G(x,y,t) = \frac{1}{2\pi t} exp\left(\frac{-(x^2+y^2)}{2t}\right), \quad (1)$$

$$T = \frac{I^-_{<=T} + I^-_{>T}}{2}, \quad (2)$$

If ants are too close, it still may result in one unified blob. To solve these conflicts, the centroids of each region on the previous frame are used. If two regions were merged, and thus one centroid is missed in the current frame, the watershed algorithm is used to split the regions starting from the previous centroids.

2.2. Tracking

Algorithm 1 Multiple ant tracking from video

```
Initialize paths from the regions found on edges of the first frame
for each frame do
    Segment each region r
    Predict current region r̂ for each known path
    Find the best correspondence < r, r̂ >
    for each path p with a correspondence do
        Update p with r
    end for
    for each path p with no correspondence do
        if there is no correspondence for p in last N frames then
            Close p
        else
            Update p with r̂
        end if
    end for
end for
```

Each ant can be represented by a path, an ordered set of regions from a set of frames. As the software is intended to work for a continuous analysis in time, for several ants, it is important to associate each ant to a path, and define when ants arrive and leave the visual field. Given that different ants are visually similar, the assignment problem is defined by comparing mainly their paths instead of similarities of the objects along the frames.

The proposed algorithm is described in Algorithm 1. Ants that are detected in the edges of each frame start a new path. As the video is processed frame by frame, the regions detected in the new frame are either associated with active paths or create new paths. For each path, a synthetic region is predicted from the last frames using a Kalman filter [40]. This filter is widely used in tracking to predict the state of the object (position and velocity) from previous frames. Then, each detected region can be compared with the predicted state to find the optimal correspondence between current frame regions and known paths. If a region is not plausible to match any known path, a new one is created with this region as the initial step, with an unique identifier. If a path is not matched with a new region in the current frame, the predicted region is assumed as the next step in the path. If this situation is repeated for a certain number of frames, or if the last recorded region is close to the frame edge, the path is closed.

The area of a region is also used in the comparison to improve the assignment problem solution. This helps to resolve assignments when paths are too close. Also, a maximum threshold distance between assignments is set, thus any candidate region that exceeds this value is discarded. The Hungarian algorithm is used to solve the optimal assignment problem between trajectories and new regions.

2.3. Ant Load detection

The load carried by an ant is often difficult to detect at a frame basis. As seen in Fig. 2, the ant is usually partially-occluded, and color differences tend to be subtle. We propose a multi-instance classification approach, where all the regions corresponding to one ant are considered as multiple observations, which will have the same binary target: either loaded or not. The set of all the regions related to each ant is obtained from the previous segmentation and tracking stages. Generally the load is larger than the ant, so an area greater than the segmented region is required to recognize it. For this reason, an extra pixel margin is added by extending horizontally and vertically from the ant bounding box, defining a larger square bounding box. Regions positioned near the edges of the image are discarded, under the assumption that they are partially out of frame

The proposed model is composed of a CNN-based network that receives each region from an ant trajectory as input. This network is trained to learn specific features of each ant boundary and predict if it is loaded or not. The first stage is composed of three blocks of convolution-pooling-batch normalization which will perform the extraction and encoding of characteristics of each observation (each frame). The output is flattened into a vector of 4608 features, which enter a fully connected layer of 64 neurons, with a ReLU activation function. 50% dropout is applied during training to regularize the network at this stage. The trainable weights are shared among observations: each image goes through the same layers, and a binary logit score is obtained for each one. A final average operation aggregates the results of the observations to obtain a classification score for the incoming pattern.

Given that the number of examples is rather low, and the imbalance between the classes is high, with loaded ants as the minority class, a data augmentation algorithm was implemented. It creates new patterns by performing random rotations (up to 180°), zoom in and out (up to 20%), horizontal and/or vertical image shift and image mirroring. The binary cross entropy is used as the loss function. To update the weights, Adam algorithm was used with a learning rate of $1e^{-4}$.

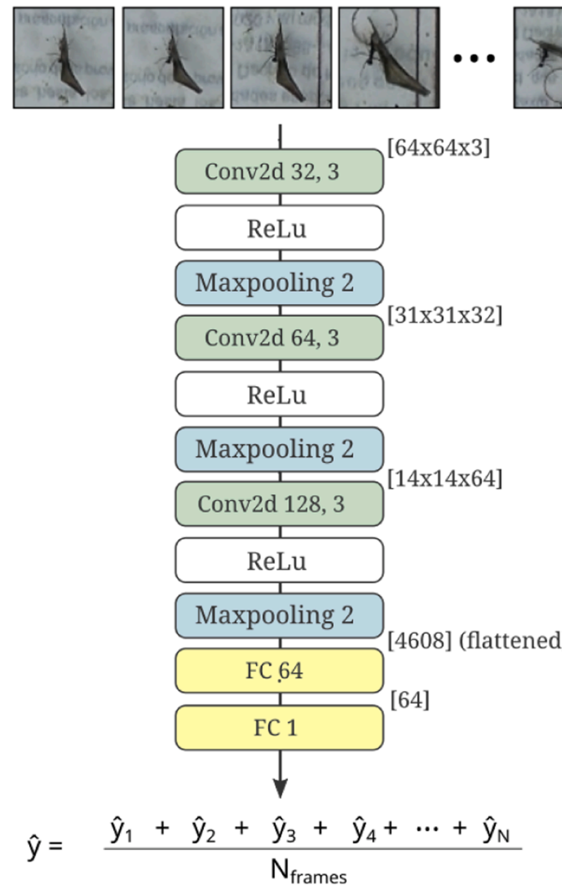

Fig. 2. Convolutional neural network for multi-instance classification. Each image (one frame corresponding to one ant) is passed through the net and the binary label loaded/not-loaded is asked as output. Then, the final score for each ant is computed as the average across all the frames of the given ant path.

3. Experimental setup

3.1. Data collection

The hardware AntVideoRecorder [38] was used to record the activity of leafcutter ants on video. The device was placed on an ant trail near the nest entrance. A white sheet was used to enhance contrast and provide size calibration. The AntVideoRecorder allows recording in a range of video resolutions. We found that 1084×720 is a good balance of image quality and autonomy, costing about 64 Gb per day. Storage is important because for the current version the videos are retrieved and processed on an external workstation.

To validate the proposed methods, a human labeling process was performed to obtain the region of each ant per frame, an unique ID across frames and a load label for each ant. The existing tagging software was not enough help in reducing the burden from the labeling process, thus we implemented our own labeling system, the AntLabeler. This tool provides an assisted labeling process specifically for this task. Starting with the raw video, an initial automatic background removal and segmentation is performed. Then the user can fix segmentation errors and id each ant on a frame. The next frames will be labeled automatically using the closest centroid from the previous label. The user will review if the tracking is correct along the ant path and tag if the ant is loaded or not. The resulting ground of truth masks are more precise than using bounding boxes, with low time cost given the automatic assistance. The fully tagged dataset sums up 4 min 45 s (8570 frames) of daytime activity with 147 ants in total (14 loaded), where each pixel on the sheet surface represents 0.1 mm.

3.2. Model validation

To validate the segmentation stage, each pixel is assigned as class 'ant' or 'background'. Taking the groundtruth labeled by the users and the prediction of the background removal algorithm, true positives (TP) are then pixels correctly classified as 'ant', thus we can define precision and recall as

$$P = \frac{TP}{TP+FP}, \; R = \frac{TP}{TP+FN}.$$

Given the tracking algorithm capabilities, it is better to have improved recall (this is, retrieve most of the ant area) than precision, thus we use a the F2-score as an integrative metric

$$F_2 = (1+4)\frac{PR}{4P+R}$$

To evaluate tracking performance, we use the CLEAR-MOT metrics: the MOT precision and the MOT accuracy [41]. The best correspondence between each predicted track and the references is matched using the Hungarian algorithm. The Housdorff distance is used to find the nearest paths. In this case, objects with no predictions are false negatives, predictions with no references are false positives and confusing one ant path with another is marked as mismatching associations between frames.

The CLEAR-MOT metrics are defined as

$$MOTP = \frac{\sum_{i,t} d_t^i}{\sum_t c_t}, \text{ y}$$

$$MOTA = 1 - \frac{\sum_t m_t + f_{pt} + mme_t}{\sum_t g_t},$$

where d_t^i is the distance between predicted and assigned track, c_t is the number of assignments, m_t, f_{pt} and mme_t are the number of false negatives, false positives and association errors respectively, while g_t is the total number of objects for each frame t. The MOTP indicates the margin of error of the tracker when estimating the precise positions of the objects under analysis. The MOTA, on the other hand, evaluates its ability to recognize object configurations and their trajectories consistently.

For the load classification stage, the dataset was split into training (80%) and test (20%) groups. Training data was split following a 3-fold cross-validation to adjust the network hyperparameters (number of convolutional filters, dropout, optimizer and learning rate, number of frames to assess). Once the final model is selected, the network was trained on the whole training data, and it was evaluated on the test data.

4. Results

Results for the background removal are shown in Fig. 3. Taking each pixel as an ant (positive class) or background (negative class), precision, recall and F2 are computed for the three methods: GSOC, MoG and Median filter, on all dataset frames. Average frame time for each method is also included. Results show that the Median filter can generate less false positives. However, MoG has a better F2-score, also with better computational cost. GSOC doubles the computational time of MoG without improving the results. Given that higher recall is preferred (also reflected in F2-score), MoG was selected as the background removal algorithm. As the software aim is to be able to process several hours of video, computational cost is an important aspect, which is also bested by MoG method.

The proposed tracking algorithm with different variations was evaluated on the segmented frames. Table 1 shows an ablation study with the results for the assignment problem with the tracking algorithm alone (plain), adding the predicted area as a feature, adding the Kalman filter predictions, and finally combining all together. As ant behavior does not follow linear patterns most of the cases, predicting their next step is difficult. Still, results show that a slight improvement is obtained when considering Kalman filter predictions in the assignment. A similar effect is observed by taking the segmented area: many of the ants are expected to be of a similar size, but taking the area into account (mainly for the ones with a load or with different body size) adds some information to the assigned problem.

For the load prediction task, two approaches were evaluated: a trajectory-based approach, which involved constructing a feature summary for an ant's entire trajectory and then detecting load possession based on it; and a frame-based approach, which involved detecting load possession in each individual frame with a set of features and then aggregating the results per ant. A set of features was computed, including Hu moments, RGB components, area and velocity statistics. As a baseline, these were used to train classical classifiers: multilayer perceptron (MLP), logistic regression (LR) and support vector machines (SVM) [42]. We found that the trajectory-approach did not yield F1 scores higher than 0.4, presumably because of the high variability of features along the path.

On the other hand, employing a late integration approach that relies on individual frame classification results produced superior outcomes for classical methods, as shown in Fig. 4. The CNN classifier was implemented using this approach, as illustrated in Fig. 2. Instead of computing handcrafted features, the network is fed with each ant bounding box, enabling it to learn meaningful features and generate a load score for each frame and ant. The predicted load scores for each ant track are then averaged to obtain an overall score. The average F1 score, depicted in Fig. 4, reveals a significant improvement in load detection,

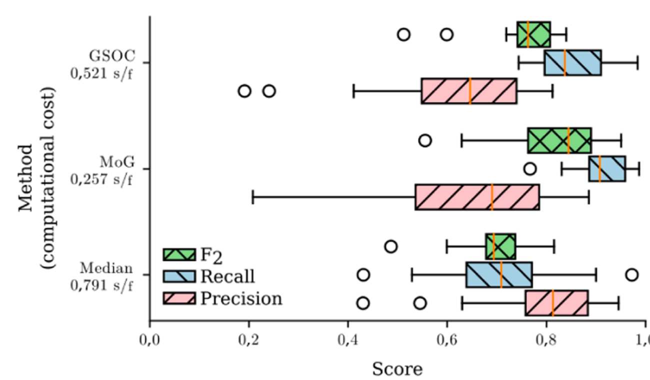

Fig. 3. Background removal scores (precision, recall and F2) measured on every frame.

Table 1
Ablation study of tracking algorithm using the plain assignment, adding the segmented area for track, and the Kalman filter prediction. MOTA and MOTP are the median values for the dataset.

Assignation algorithm	MOTA	MOTP
Plain assignment	0.960	7.020
Using area only	0.971	7.048
Using Kalman filter only	0.970	7.297
Using area + Kalman filter	0.971	7.046

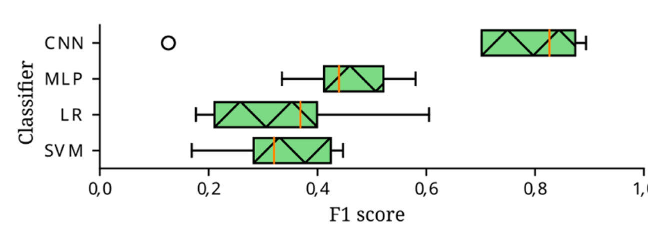

Fig. 4. F1 score for load prediction using extracted features (MLP, LR, SVM) and a deep learning approach (CNN). Boxes are the scores per video in the test partitions.

with a median value of 82%.

This software was tested in a field application under a research project which aims to know the locomotion and forage rhythms of *Acromyrmex lundi* in Oro Verde, Argentina. For the study, the AntVideoRecord was used as a video capture device, obtaining more than 189 days of recorded data from March 2021 to the present. The videos were collected weekly and processed using AntTracker. Fig. 5 shows the average number of ants entering (red) and leaving (black) the nest for the first, second, and third month of spring. The temperature (blue) is also registered by the AntVideRecord. These plots show two main activity peaks: one during the morning, and the other at evening. Also, the rhythm of activity was different at the beginning compared to the end of spring, possibly because the ants still have the memory of activity stored in their internal biological clock for winter. As the season progresses, the photoperiodic and temperature conditions change, and consequently a new rhythm of daily activity is established. This allowed a priori confirmation not only that the rate of locomotor activity is seasonally associated, but also the nest dynamics within the season can be studied. These preliminary field results show that the design is reliable for the LCA behavior monitoring using AntVideoRecord's hardware and AntTracker, making it a device that certainly will improve the knowledge in ecological science.

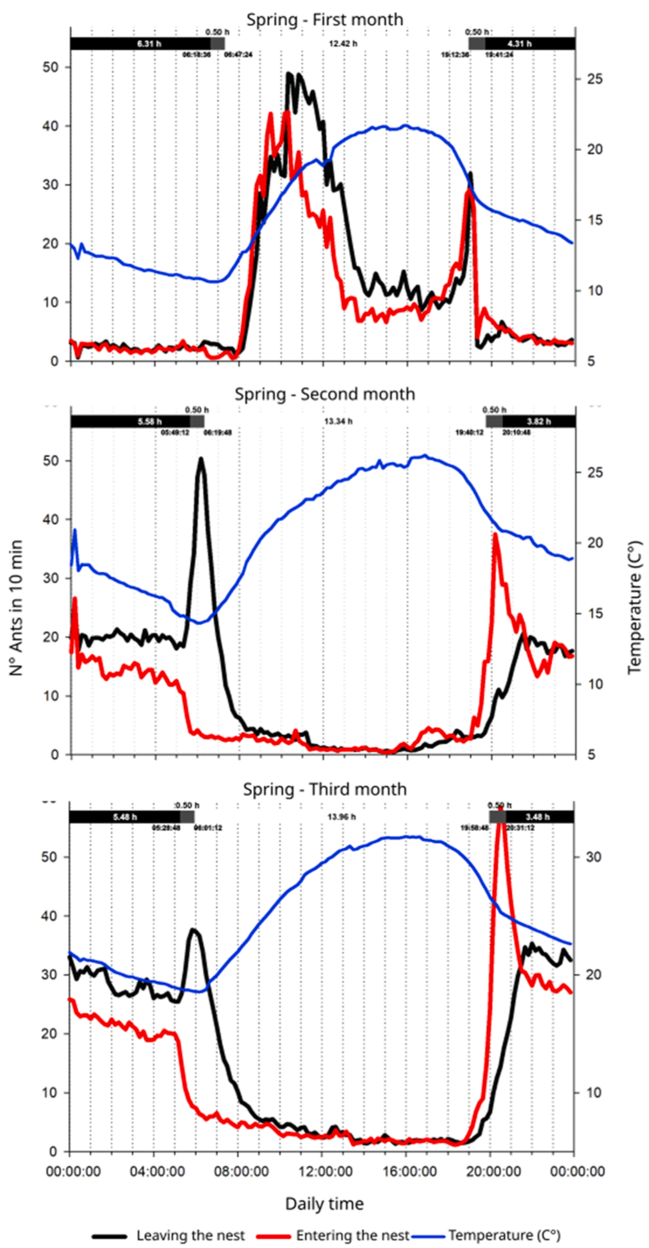

Fig. 5. Average ant counting for different times of a day, on the three months of spring. In red the ants entering the nest, in black ants going out the nest, and in blue the temperature.

5. Conclusions

In this work a comprehensive solution is proposed to track ants behavior in the wild. Using AntVideoRecord, an economical and open video acquisition hardware, ants can be recorded in their natural trails. Background removal, ant segmentation and tracking can be automatically performed using the proposed methods. The ants that carry a load are detected using a convolutional neural network, giving a new way to analyze foraging behavior in the future. With the detailed timestamps from using AntVideoRecord + AntTracker it is possible to obtain a clear picture of the ant behavior along other variables such as daytime, location and climate. The proposed methods were tested against human labeled data. Both the main software tools and the labeler (AntLabeler) are now available as open source tools.

A wider validation process is being conducted in collaboration of agricultural sciences researchers to assess the precise foraging behavior on a much larger scale video recording. The future work will validate this approach for the estimation of foraging activity, using a larger tagged dataset and an estimation of load capacity of the ants under study.

Availability

The source code to use this tool is available at https://github.com/lbugnon/AntTracker.

CRediT authorship contribution statement

Julian Alberto Sabattini: Conceptualization, Validation, Investigation, Resources, Data curation, Supervision, Writing – review & editing. **Francisco Sturniolo:** Software, Investigation, Visualization. **Martín Bollazzi:** Writing – review & editing. **Leandro A. Bugnon:** Conceptualization, Methodology, Investigation, Supervision, 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

Source code is freely available.

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