A Computational System to Support fully Automated Mark-Recapture Studies of Ants

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***Abstract*—Ants are ubiquitous insects that have great significant for humans. In agriculture they can suppress pest populations and aerate the soil, but they sometimes *protect* pests, leading to billions of dollars of crop loss. As such, there is a growing need to study these insects, both in the lab and in the wild. In this work we describe an end-to-end machine learning/robotic system to physically capture individually marked insects. To the best of our knowledge, this is the first system described in the literature that can capture individually targeted insects, without harming them, allowing them to be recaptured multiple times.**

Keywords—image processing, robotics, applications of AI

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I. INTRODUCTION

Ants are extraordinary prevalent insects; it has been estimated that ants make up approximately 20% of the biomass of all terrestrial animals [8]. Unsurprisingly, ants have a significant impact on human affairs. On the positive side, ants aerate soil, act as seed dispersers and can control agricultural pests [7]. On the negative side, ants aggressively protect Asian Citrus Psyllids, which cause billions of dollars of crop loss to the citrus industry each year [3]. Given their economic (not to mention scientific), importance, scientist worldwide have developed an arsenal of digital tools to help study ants, both in the lab, and less commonly, in the wild. There are video processing tools to measure how far a collection of ants walk [6]. Such tools track only global summaries, as it is near impossible to track individual ants, because two ants may climb over each other when they meet. As shown in Figure 1, to count individual insects, entomologists typically mark them with daubs of paint. With four easily differentiable colors, and two locations (head and abdomen), and entomologist can track up to sixteen individual ants.

While individually marked ants can be *digitally* recaptured using this technique, there is currently no automatic technique to *physically* recapture them in the wild. It is possible that a patient entomologist could simply wait for the marked ant to reappear. However, ant colony sizes can be in the tens of millions [1], and the nest may have multiple entrances, this is clearly not a practical option.

Figure 1: A marked Field Ant (*Formica francoeuri*) with a coin for scale. A US penny is 19mm in diameter.

In this work we introduce an end-to-end system that allows individual ants to be marked, released back into the wild, and physically recaptured, possibly days, weeks or months later. Our system consists of a simple and inexpensive robot that can be left unattended in the field to wait for the marked insect to pass within the field of view, then uses a short burst of vacuum pressure to suck the ant into a collection chamber, where it can be retrieved at leisure.

II.BACKGROUND

Give the important of insects in human affairs, from pollenating half the food we eat, to spreading insect-vectored diseases, there is a rich literature on using image/video processing to accelerate entomological research (see [4] and the references therein). However, to the best of our knowledge, this work is the first to proposed and end-to-end system to *physically* recapture targeted insects.

It may not be obvious as to *why* an entomologist would need to physically recapture targeted insects. We are providing a general tool, and are strictly agnostic to such considerations, nevertheless, we will briefly provide some motivating examples.

In just the last few years several studies have emerged showing that individual ants have *personality*. For example, [4] O'Shea-Wheller, speaking of his recent study on nest choice behavior in ants notes that "*Some ants are picky, others are more liberal and will accept almost anything*" [5]. Clearly studies that investigate personality differences may need treat insects with personalized interventions.

III.ROBOT AND ALGORITHMS

There are several constraints on the design of our insect handling robot. The first is simply cost. For some applications of our system, the robot will need to be left outdoors and unattended for days. An expensive robot would be a magnet for theft, and a painful loss. A secondary concern is that the robot is able to capture the insect without harming it. Recall that for some studies, the entomologist may wish to capture the same insect multiple times, perhaps to feed it a special diet. This requirement excludes any robot that uses a classic gripper "hand". While experienced entomologists can grab ants with forceps without harming them. Reproducing that skill in a robot would be very challenging, and in any case overrun our low-cost requirement.

Our solution to this problem is bio-inspired. Many fish species (bass, trout, pike, etc.) capture their living prey with powerful suction, expanding their mouth and pharynx rapidly to suck the prey in before biting down and swallowing [2]. As shown in Figure 2, we have designed a simple robot that works on the same principle.

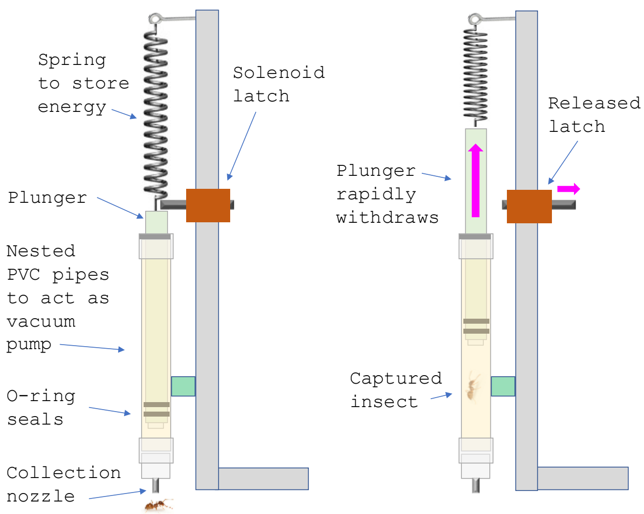

Figure 2: A schematic of our insect capture algorithm. *left*) The device in "cocked" position. The energy to power the vacuum bust is stored in a spring. *right*) When our classification algorithm observes the targeted insect, it signals a solenoid to retreat, firing the vacuum plunger upwards and creating a vacuum at the collection nozzle, sucking in the insect.

Our robot costs only $20 in materials, and can be build with very common woodworking tools in under an hour. Note that our robot is static, it does not move to the insect. Such a mechanism to steer the collection nozzle would be prohibitively expensive. This may seem like an issue, but the following two observations mitigate such concerns. It has long been known that ants are unwilling to walk on surfaces that are painted with Polytetrafluoroethylene (PTFE) more commonly known as liquid Teflon. Thus, we can paint arbitrary guidelines to "corral" the insects to walk past the collection nozzle. Secondly, we can simply position the robot directly over nest's entrance, meaning an entering or emerging ant must pass by our field of view.

IV.EXPERIMENTS

Our insects of interest are *Formica francoeuri* (No official common name, but often called *Field Ant*), native to the West Coast of the USA. For concreteness, in Table 1 we show the actual code we use to trigger capture. Note that this code has some hardcoded parameters, these are *learned* offline on training data collected in the same conditions.

Table 1: The code used to trigger the robot shown in Figure 2.

```
function [boolean] = isPositive(FILENAME)
    % Load image and scale RGB values on a scale from 0 to 1
Image = double(imread(FILENAME))/255;
RED_IDX = 1;  , GREEN_IDX = 2; , BLUE_IDX = 3;
    % Check for pixels with high R values and low G and B values
    % Set all pixels that meet these parameters to white (1)
    % Set all other pixels to black (0)
 HighRed = Image(:,:,RED_IDX) > 0.7 & Image(:,:,GREEN_IDX) < 0.15 &
Image(:,:,BLUE_IDX) < 0.15;
    %Find average color of entire image on a scale from 0 to 1
 MeanColor = mean(HighRed);
 ImageAverageRed = sum(meanColor)/numel(meanColor);
    % If average color of image is greater than 0.005, then there
    % is sufficient red in the image and the function returns true.
    if (ImageAverageRed < 0.005)
        boolean = true;
    else
        boolean = false;
    end
end
```

Using this function embedded into a leave-one-out classifier with a class balanced dataset consisting of 100 images, we found the accuracy to be 98%. The two errors where both false positives, apparent causes by poor lighting.

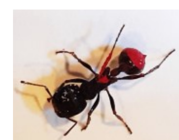

Figure 3: A sample true positive

V.CONCLUSIONS

We have introduced what we believe is the first system capable of capturing individually targeted insects. We believe our system will spur a host of follow-up research in machine learning, to generalize the capture missions supported.

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