FOOTPRINT RECOGNITION OF RODENTS AND INSECTS

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ABSTRACT

In today's pest control operations large numbers of tracking tunnels are used to estimate the number of rodents present in the target area, providing a basis for planning the required amount of poison. The marks left in the tunnels have to be interpreted by trained experts. This article introduces two methods that make a step towards automating the process of recognizing footprints of rodents and insects. Furthermore two classification methods (Principal Component Analysis, a simple Naïve Bayes classifier) are studied to distinguish the four examined insect species. Here, a combination of both classifiers proved superior to using just one method.

1. INTRODUCTION AND BACKGROUND

We start with a brief overview on the history of rodent eradication programs in New Zealand. Then we introduce the approaches to recognize and classify rodent and insect footprints in Sections 2 and 3. Section 4 ends with a brief discussion.

The four rodent species present in New Zealand are Norway rats (*Rattus norvegicus*), ship rats (*Rattus rattus*), house mice (*Mus musculus* or *Mus domesticus*), and kiore (*Rattus exulans*). With the aid of cats (*Felis catus*) and stoats (*Mustela erminea*) they caused the extinction of at least 45 bird species in New Zealand.

1.1. Eradication

To counter these developments New Zealand authorities introduced eradication programs at the beginning of the last century, first targeting large animals like deer, cattle and goats. Later numbers of smaller animals, namely possums and cats were massively reduced.

However, in those first years it was believed that it was impossible to completely eradicate shy, nocturnal rodents from an island. This opinion slowly changed when in the 1970s the second generation of rodenticides became available. In 1982 Ian McFadden was assigned the task to develop a method to clear small islands of rodents. With Ruruma Rocks in the Bay of Plenty, the new era of rat eradication began [1].

While the first islands were cleared using hand-placed bait stations, slowly the technique evolved to sprinkling the poison across an island and finally to distribution of bait by helicopters. This enabled the Department of Conservation to target larger and larger islands, until in 2001 the largest rat eradication programme to date was carried out on Campbell Island, New Zealand. There 200,000 Norway rats were killed on 11,300 hectares using 120 tonnes of poison. In 2003 Campbell Island was officially declared rat-free [2]. Today the eradication techniques developed in New Zealand are exported worldwide for example to the Falkland Islands, Hawaii, and Australia to name just a few.

1.2. Tracking Tunnels

Tracking tunnels are basically rectangular polyethylene tunnels designed to allow the target animal to walk through unhindered. A tracking card, made of an absorbent white cardboard, has an especially developed non-drying ink which has been screened onto a sealed section of the card. On the inked section a lure is placed (e.g., peanut butter for rats and mice). Any animal, or insect, attracted into the tunnel after walking across the ink leaves footprints on the absorbent end section of the card. The oils within the ink are absorbed into the cardboard leaving tracks which can be analysed. They may reveal the genus or species, and possibly the sex of the creature [3].

Tracking tunnels are used to monitor abundance of small mammals. Typically a field study is conducted prior to an eradication operation. Afterwards the study is repeated to check the effectiveness of the implemented procedure. This method was effectively implemented on the Falkland Islands [4], on Maui in Hawaii [5] and in various places in New Zealand [6]. Tracking tunnels have also been used to investigate the enormous fluctuations of rodent populations both between seasons and over the years. Fluctuations as high as 90% can be observed between summer and winter [7]. This observation leads directly to the question how meaningful are measurements made with tracking tunnels.

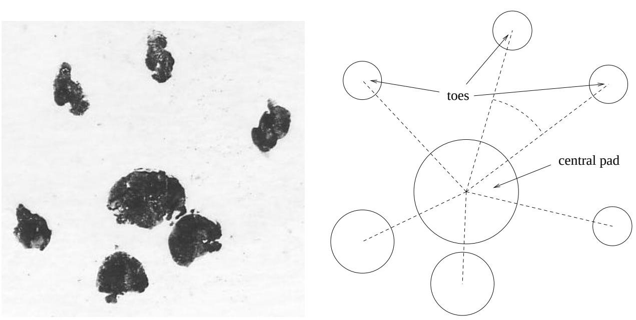
In his field study on Maui, Hawaii Brosius et al. observed a good correlation between visitation rates of the tunnels and population density of rats [5]. However Russell notes that this linearity could not be found for mice [8]. Additionally it has to be noted that only relative numbers can be reliably measured [9].

2. RODENTS

This section introduces approaches to identify footprints of rodents on tracking cards and how to connect footprints to strides.

2.1. Footprint Recognition

The footprints of rats and mice are fairly circular in shape with the toes surrounding a central pad (see Figure 2.1.3 (a)). So the approach is to first search for possible central pads. These are then used to start an exhaustive search in the neighborhood of these pads for a valid foot configuration.



(a) Rat front foot (b) Template for rodent foot

Fig. 1. Rat foot with its template

The validity of a blob configuration is determined by comparing it to a template (see Figure 1 (b)) that was generated semi-automatically beforehand. Such a template is comprised of minimal and maximal areas of all toes, their distances to the central pad, and the angles to their two neighbors. For the central pad the length and width of a matched ellipse is also noted.

2.1.1. Implementation

We start with binarizing an image of a scanned tracking card. (The threshold for binarisation was set to 210; considering that the values can range from 0 to 255 this is admittedly quite a high value but as the footprints especially of mice are sometimes quite weak a high binarisation threshold is rather advantageous.)

Next contours are extracted from the binary image using a standard algorithm as described in [10].

Then all contours whose area is considered to be too small (less than 20 pixels) are ignored for the rest of the algorithm.

Ellipses are fitted to the remaining contours in a least-square-error manner as described in [11].

This finishes the preprocessing. The algorithm now tries to find central pads of all footprints. To this end the areas of all contours and the parameters of the corresponding ellipses are compared to a lower and an upper threshold. All blobs that satisfy this chosen criterion are then marked for further processing. The gathered information is unfortunately not sufficient in general to identify central pads at a high rate. But it limits the number of candidates significantly. However, in combination with toe recognition (described in the following), reasonable results can be obtained.

Around each preliminary central pad we try to identify likely toes. A first filter that is applied uses minimal and maximal distances for each toe to a central pad, which are stored with the template, as its discriminating element. Only contours that fall between these thresholds are further processed.

If there are not enough toes in the vicinity of a potential central pad then this cannot be a footprint. It may be possible to relax this constraint in future versions though because, if the footprint is very faint, a toe might not show up or get eliminated by our thresholding of regian areas. If the rest of the footprint gives sufficient evidence to identify it, it should be recognized even in spite of missing toes.

Next angles defined by a lines from each toe to the central pad are calculated with respect to a reference coordinate axes and the toes are ordered according to this angle (see Figure 1(b)).

Finally the algorithm can attempt to find the best configuration of blobs surrounding the central pad that matches the given template. As the conducted search is exhaustive, we are guaranteed to find the best combinations of toes.

A configuration is evaluated by comparing the distance of every toe to the central pad and the angles with the central pad to its neighbors with a given template. We define a configuration's evaluation

$$E = \sum_i a(x_i) \tag{1}$$

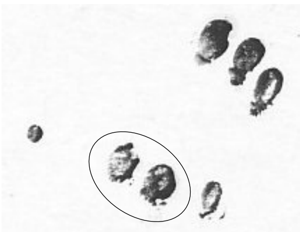
with

$$a(x_i) = \begin{cases} \frac{x_i - min_i}{mean_i - min_i} & \text{if } x_i \le mean_i \\ \frac{x_i - mean_i}{max_i - mean_i} & \text{if } x_i > mean_i \end{cases} \tag{2}$$

where min_i, max_i, and $mean_i$ are the parameters of the template and the x_i is the value of the potential footprint.

2.1.2. Splitted or Merged Central Pads

One of the problems encountered is illustrated in Figure 2. On the left, the print of the central pad of a mouse hind foot is split. In about the same number of cases the central pad can appear to be merged. A simple and effective solution to this problem is to introduce different templates for splitted and merged versions.



(a) Split central pad

(b) Merged central pad

Fig. 2. Hind feet of mice.

2.1.3. Right vs. Left

The same approach can be taken to distinguish left and right footprints. Even front feet of rats which are very symmetric (see Figure 2.1.3) can be distinguished because the pads behind the central pad have a different distance to the central pad. Front feet of mice however are even more symmetric (compare Figure 2.1.3) and thus remain an unsolved problem.

(a) Mouse front foot

(b) Rat front foot

Fig. 3. Front Feet

2.2. Making Strides

Strides are useful to determine the gender and estimate the size of the rodent.

The idea to achieve this objective is to compare distances and orientations of footprints to connect them into a network of strides. The relative positioning is the angle between the connecting line of two footprints and the respective orientations of the footprints. This may also be an important property.

The implementation of this idea is fairly straight forward. Firstly the two feet which form a stride have to be on the same “corner” (i.e., left-front, right-front, left-back, or right-back) of the animal. Furthermore the distance between the feet must not exceed, or be inferior to some thresholds. The two feet must also point in approximately the same direction. If all these criteria are satisfied then the connecting line between the two feet is also considered. The angles between this line and the two feet’s direction must likewise not surpass a threshold.

2.3. Results

The algorithm to identify rodent footprints was verified for tracks collected on four tracking cards (two with mouse footprints and two with rat footprints). All templates were applied to all images. The classified footprints were manually categorized as ”correct,” ”false positive,” and “true negative”. The results are summarized in table 1.

	mice	rats
Correct	18	17
False positive	11	2
True negative	13	9

Table 1. Performance of Footprint Extraction

The result indicates, that the algorithm is good on identifying rat footprints. A false positive rate of 11% is less than what we have expected. However, this comes at the expense of a higher false rejection rate. Also note that the number of missed footprints is rather subjective. The real number of footprints is substantially higher and the number of footprints that the algorithm is expected to be able to identify is lower because it cannot handle missing or merged toes, or a very distorted central pad. Instead, the field indicates the number of footprints that we were able to identify by looking at the images.

Footprint recognition for mice proved to be more complicated. The rate of false positives is high (38%) which is especially critical since almost 42% of all footprints were missed. However, the same hesitancy should be taken when interpreting these results as the same procedure was used for obtaining them as for the rat footprints.

3. INSECTS

This section describes our initial approach for identifying insect footprints. As a first approach proved less successful than expected, two different approaches to the extraction of footprints will be explored as well. Used classifiers are briefly introduced. Then we touch on a variation of the stride recognition algorithm. Finally we describe experiments that were conducted.

3.1. Initial Approach

Our first approach was to apply the above algorithm that was successful for rodents, with only a minor modification for insect footprints.

As some insect's footprints closely resemble broken straight lines (see Figure 4) this approach focuses on recognizing more or less straight line segments. Then properties like area, length, and width are used to identify the species causing the print.

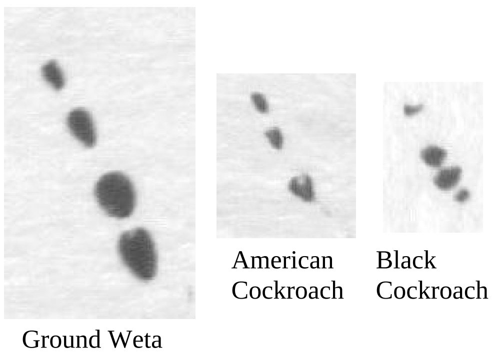


Fig. 4. Example insect footprints

The first two processing steps are the same as in footprint recognition for rodents. First, the image is binarised. Second, small contours are filtered out (here all blobs with an area less than 5 pixels were eliminated for most insects).

Then all contours that are within a certain distance to each other, and that have a major axis facing in about the same direction, are connected. A blob is defined to have a major axis if it has a sufficiently large area and the ratio of width divided by the length of a fitted ellipse is above a threshold. This was necessary because if the orientation of all blobs was taken into account, hardly any connection could be established also allowing that small blobs can be added even if they have a different orientation.

Next, footprints from all blobs that are not connected are created. Every blob that is not connected features an area that is in a specific range (for black cockroaches 700 to 1000 pixels) and has a major axis is made into a footprint.

Next more complex footprints are 'grown.' Here adjacent connections are added to a footprint if they are oriented in a similar direction.

At last, all footprints that are too small (too short, not wide enough, or with an insufficient area), or that have an inappropriate length-width ratio, are deleted. The remaining footprints will be truncated if they are too big (too long, too wide, or with a too large area). Truncation in this case means that an area-wise smaller blob at one of the two ends of a footprint is removed.

3.2. Second Approach

This second approach to recognizing footprints of insects was developed because of the poor recognition performance of the first algorithm. Specifically the greatest problem with the first approach is that the search space can sometimes be restricted randomly by competing footprints. This prevents valid footprints from emerging.

The proposed procedure basically replicates the last step of the rodent footprint recognition, after doing some preprocessing. In a nutshell, an exhaustive search in blob space for valid footprint configurations is conducted. All footprints that match the hard criteria as specified in a template get filtered by the two 'soft' classifiers (PCA and Naïve Bayes), and only the area-wise largest of a number of overlapping footprints is retained.

Next contours are filtered by first matching an ellipse to them, and then comparing the length of the ellipse's axes to maximum and minimum allowed lengths.

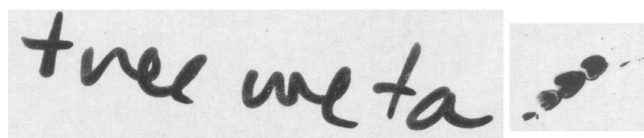


Fig. 5. Handwritten label and footprint of tree weta

As the tracking cards were labeled with the insect species, an additional step was introduced to filter out handwritten characters. This is important because very large insects, for example tree wetas (*Hemideina thoracica*) produce footprints that can be as big as handwritten characters (compare Figure 5). The relation between the area of a blob and the area of its convex hull was chosen as discriminating criterion, because most blobs of footprints are very close to convex, so the area of its convex hull is very close to its area. Handwritten characters on the other hand are rarely convex (see, e.g., the t in Figure 5) and if they are then they have a hole in the middle (for example the letter o).

Next, every blob is successively chosen as a seed, and a footprint is recursively grown around it. Growing is simpler in this approach than in the previous. All combinations of blobs in the vicinity of the seed are evaluated.

If a configuration passes length, width, and area test, then it is considered to be a valid footprint. The footprint is then tested by one or both of the classifiers described below. If they too accept the footprint as being valid then it is classified. Only the best of a number of overlapping footprints is retained. The rate of a footprint is simply its area, favoring bigger footprints.

3.2.1. *Classifiers*

Two classifiers were employed to identify insect species.

Naïve Bayes was our initial attempt of using a statistical classifier to improve recognition rates. We used the Gaussian Bayes algorithm described in [12] with a Laplace correction in place. The feature vector was simply comprised of the attributes length, width, area, and length / width.

Principal Component Analysis was then added as a more advanced (and hopefully more successful) classifier. The principles of PCA are explained in [13]. The unprocessed section of the original image containing the footprint is rotated and padded with its border color to a common size (258×514 pixels). Then it is flipped so that the darker halves are at the top and left to align curved footprints. This image is then used as the input to the PCA. The first ten principal components are then compared within a database to identify the species.

A footprint is accepted if one chosen classifier or both identify it as the same species as the target species.

3.3. Results

The greatest challenge in conducting experiments with insect footprints was finding the ground truth.

To test our algorithms we have run them for every combination of template and image without a classifier, with just the Naïve Bayes classifier, with the PCA classifier and with both. When both classifiers were working together they had to agree on the class of the tested footprint otherwise it was rejected. This way the number of false positives was kept to a minimum.

Table 2 shows the number of recognized footprints for each studied species on each image. This number includes false positives. The studied insects were American Cockroach (*Periplaneta americana*), Black Cockroach (*Platyzosteria novaeseelandiae*), Ground Weta (*Hemiandrus*), and Tree Weta (*Hemideina*).

	image			
insect	Am. C.	Black C.	G. Weta	Tree W.
Am. C.	30	3	6	10
Black C.	3	57	0	0
G. Weta	4	4	12	4
Tree Weta	2	5	7	19

Table 2. Footprint counts using both classifiers

Overall this last variant proves to "possess sufficient discriminating powers" to distinguish between the four targeted insect species. However, this result must be approached with caution as our experiments so far were only done for a few images.

3.4. Small Steps

Footprint connection to form strides was done in a very similar manner to the connection of rodent footprints. First footprints on one side of the insect are grouped together. Then connections across the body of the insect can be made.

3.4.1. *Approach*

Insects usually set their feet in a certain orientation relative to the direction of travel. Two footprints on the same "corner" (or middle) of the insect will point in about the same direction but at an angle to the direction of travel (see Figure 6). If the approximate stride length and this angle are known then connecting them is relatively straightforward.

The connection of opposite sides of the insect can be accomplished because we know the direction of travel and the corner of the animal. The opposite side we want to connect to will have to be the same front, middle, back, at a certain distance, at a certain angle. Additionally the direction of travel of the questioned footprint must be approximately the direction of the current footprint mirrored on the direction of travel.

Figure 6 shows results of applying this procedure to an actual image. It shows the trail of a black cockroach crossing the image from top to bottom.

Connecting footprints of one side of the insect with those on the other side was tuned to produce as few false connections as possible. Configuring the thresholds more broadly results in more connections but also in a significantly increased rate of false positives.

4. CONCLUSION

After giving a short overview of the history of pests and pest control in New Zealand two methods were introduced aiming to automate the process of footprint extraction and recognition from tracking cards as they are used in tracking tunnels.

The first procedure was designed to recognize footprints of rats and mice. However it may be possible to extend it to recognize footprints of other small mammals such as stoats or hedgehogs just by adding more templates.

We realized that insect recognition does not follow the principle of rodent footprint recognition. This is mostly due to the fact that the footprints are smaller and exhibit less developed patterns.

Insect footprints are frequently falsely spotted in areas that a human might classify as drag marks. So another idea

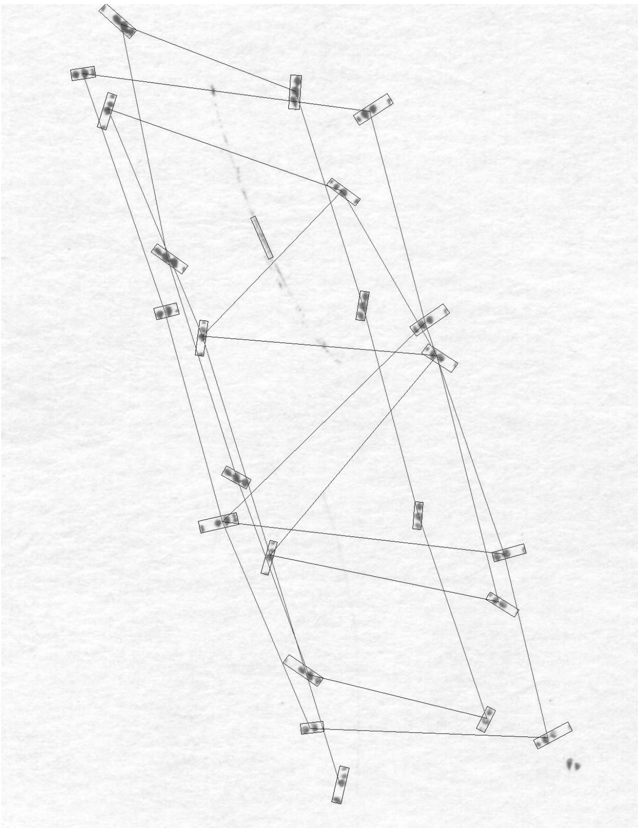


Fig. 6. Connected footprints of American Cockroach.

to improve accuracy of the insect footprint extraction algorithm is to identify drag marks first and then exclude them from the search similar to the way text is excluded before the actual footprint extraction begins.

The experiments, still limited their extent, provide already some evidence that it might be possible to automatically identify marks left by small animals in tracking tunnels up to a reasonable percentage.

5. REFERENCES

[1] I. McFadden, "Rat-free islands," *Forest and Bird*, p. 18, 1996.

[2] E. Marenzi, *Conservation Action*, chapter Biosecurity, Department of Conservation, Wellington, New Zealand, 2003.

[3] "Connovation - equipment instructions," 2004, (Accessed: 5 May 2004) `http://www.connovation.co.nz/mainsite/EquipmentInstructions.html`.

[4] D. Brown, L. Chadderton, and K. Brown, "Rat eradication," 2002, (Accessed: 4 May 2004) `http://www.falklandsconservation.com/wildlife/ conservation_issues/rat_eradication-final.html`.

[5] C. N. Brosius, T. R. Malcolm, B. D. Sparklin, and M. M. Okada, "The effectiveness of tracking tunnels in monitoring the control of rat species (*Rattus spp.*)," (Accessed: 3 August 2004) `http://www.state.hi.us/dlnr/mfbp/tunnel-tracking.php`.

[6] Department of Conservation, *Managing rodents on the New Zealand mainland? What options are currently available?*, DOC Science Internal Series, Wellington, New Zealand, 2001. Department of Conservation.

[7] J. G. Innes, *Ship rat*, *The Handbook of New Zealand Mammals*, pp. 206–225, (King, C. M. Ed.), Oxford University Press, Auckland, New Zealand, 1990.

[8] J. Russel, "A recent survey of methods for closed populations of small mammals," unpublished dissertation to STATS776 Animal Abundance Course (A), 2003.

[9] E. Rexstad and E. Debevec, "Power and cost considerations for small mammal monitoring," Tech. Rep., Institute of Arctic Biology, Fairbanks, Alaska, 1999.

[10] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis, and Machine Vision*, Brooks/Cole, Pacific Grove, 2nd edition, 1999.

[11] A. W. Fitzgibbon and R. B. Fisher, "A buyer's guide to conic fitting," in *Proc. 6th British Conf. on Machine Vision (Vol. 2)*, Birmingham, United Kingdom, 1995, pp. 513–522, BMVA Press.

[12] A. Webb, *Statistical Pattern Recognition*, Wiley and Sons, New York, 2nd edition, 2002.

[13] B. Jähne, *Digital Image Processing*, Springer, Berlin, 4th edition, 1997.