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Automatic track recognition of footprints for identifying cryptic species

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Abstract. The recognition of tracks plays an important role in ecological research and monitoring, and tracking tunnels are a cost-effective method for indexing species over large areas. Traditionally, tracks are collected by a tracking system, and analysis is carried out in a manual identification procedure by experienced wildlife biologists. Unfortunately, human experts are unable to reliably distinguish tracks of morphologically similar species. We propose a new method using image analysis, which allows automatic species identification of tracks, and apply the method to identifying cryptic small-mammal species. We demonstrate the method by identifying footprints of three invasive rat species with similar morphology that co-occur in New Zealand, including detection of a recent invasion of a rat-free island. Automatic footprint recognition successfully identified the species of rat for >70% of footprints, and >83% of tracking cards. With appropriate changes to the image recognition, the method could be broadly applicable to any taxa that can be tracked. Identification of tracks to species level gives better estimates of species presence and composition in communities.

Key words: automated species identification; binarization; index; invasive species; New Zealand; rats; Rattus exulans; Rattus norvegicus; Rattus rattus; *rodents; template matching; tracking.*

Introduction

Accurate estimates of species presence are required when ecologists study rare species or assess community composition (MacKenzie et al. 2002), and automated species identification could provide many advantages to ecologists in such situations (Gaston and O'Neill 2004). Indexing is one cost-effective method for monitoring animal populations over large areas (Whisson et al. 2005). Noninvasive methods such as tracking are particularly important when studying low-density or cryptic species that are difficult to detect by standard methods such as trapping (Brown et al. 1996, Watts et al. 2008). The principle of animal tracking is to isolate single footprints from a number of unknown footprints and to identify the species that generated the footprint. Tracks are collected by a tracking system that involves a tracking tunnel, a pre-inked tracking card, and lures placed on the center of the card. Animals attracted by lures walk through the tracking tunnel and leave their footprints on the tracking card. Traditionally, analysis is carried out manually by experienced biologists who can distinguish tracks of some different species (Ratz 1997). Unfortunately, identification among taxa with similar morphology is usually impossible (Ratz 1997, Glennon et al. 2002; Fig. 1). Uncommon species may be overlooked and classified as a more common, but similar, species, leading to negatively biased estimates of species presence or richness (e.g., Golding and Harper 2008).

We describe an automated method of differentiating tracks of small animals. Our automatic track recognition system follows three main steps: (1) track acquisition: field collection and scanning; (2) template extraction: extracting an initial template database from a given training set for future matching; (3) template comparison: querying a template database to find a comparable template and automatic track classification for classifying inputs into different classes according to their geometric characteristics. This method resolves the need

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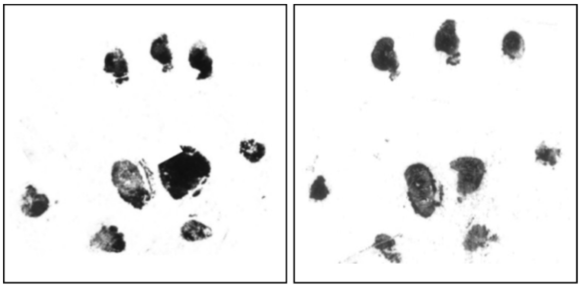

FIG. 1. (Left) Left hind print of *Rattus exulans*. (Right) Left hind print of *R. rattus*.

for experienced biologists to subjectively classify species tracks, and allows animal tracking methods to be used on a much larger scale because cards can be rapidly analyzed by any user.

Track Acquisition

Tracks must first be acquired in the field using standard field methodologies. Multiple footprints from multiple animals are possible on a single tracking card. Tracks collected from the field can appear faint (dry ink) or overlap one another (possibly from multiple animals). This requires a flexible image analysis methodology that can tolerate such difficulties. Any method will only be practical if it can correctly identify most of the clearly delineated prints, and preferably some of the more "difficult" prints. To provide computer-analyzable footprint patterns, tracking cards are scanned at 300 dpi using flatbed scanners and stored in bitmap format as gray-scale pictures. Generally, the dimensions of a 300-dpi scanned tracking card are about 1170×3500 pixels, occupying ~3.9 Megabytes of memory space.

Scanned images are segmented through an automated binarization process in order to extract patterns for recognition. The quality of recognized patterns significantly influences the subsequent analysis. In the case of animal tracks, the intensity of a footprint can vary greatly depending on factors such as the type and age of tracking media. A fixed binarization threshold over an entire card, delimiting footprints from the background, does not provide proper footprint patterns, so we implemented Abutaleb's method, which has been reliable for binarizing insect footprints (Woo 2004). However, animal footprints can have large variability in the characteristics of individual prints (on the same card). This makes a straightforward adaptation of Abutaleb's method impossible. We chose an adaptive binarization method whereby the tolerance for distinguishing footprints from cards is adjusted locally within a card, depending on the relative intensity of any particular footprint. We convert a gray-scale scanned image into a binary (black and white) image as follows: we initiate a standard scan on the gray-scale image and if the local mean and pixel values on a part of the card are within a defined small range (i.e., card background), we continue with scanning; otherwise we initiate a connected region of pixels (i.e., a footprint). This region "grows" in the order that pixels are scanned, with pixels satisfying

$$|m_{A,p} - g_p| \leq t_A$$

where $m_{A,p}$ is the sliding mean of region A (up to reading pixel p), g_p is the gray-scale image value at pixel p, and t_A is the local intensity tolerance for this region (e.g., defined by a percentage of the initiating pixel value).

The final binarization response for all pixels within a region is constrained within a biologically reasonable size for footprints. Regions of a card with value 0 (i.e., black) are treated as potential parts of footprint patterns for further analysis (Fig. 2). In many cases, fainter drag marks can connect tracks (e.g., the central pad and lumps of mammals). By manually adjusting the local tolerance in a particular area of a card, binarization can erase such drag marks and other noise (e.g., smaller insect tracks), ensuring better footprint patterns for future analysis.

All possible toes and central pads in the binarized image h are thus identified as unique regions, which are approximately circular in shape and can be reasonably represented by ellipses (Fig. 2). Pixels $p = (x, y)$ on the

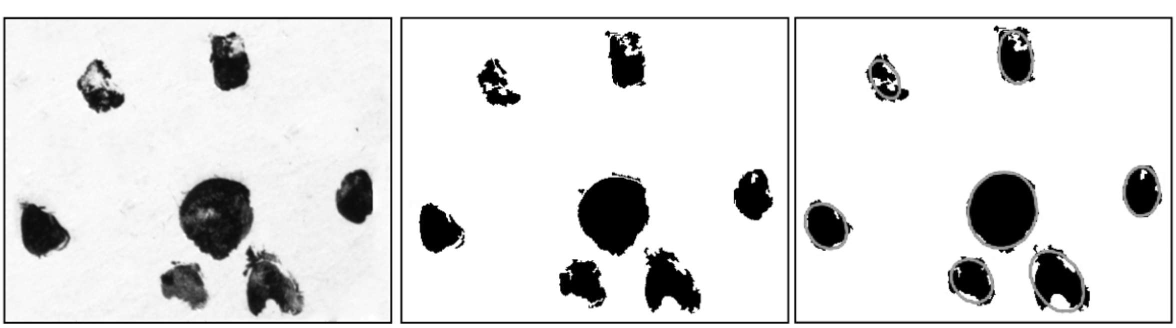

FIG. 2. (Left) Original image. (Middle) The adaptive binarization result for $t_A = 32$ (for any region A). (Right) Fitted ellipses for the binary image.

border of each of those regions are used for least-square fitting of a uniquely defined ellipse (see Fitzgibbon et al. 1999):

$$F(\boldsymbol{\theta}, \mathbf{p}) = ax^2 + bxy + cy^2 + dx + ey + f$$

where $\boldsymbol{\theta} = [a\,b\,c\,d\,e\,f\,]^\top$ and $\mathbf{p} = [x^2\,xy\,y^2\,x\,y\,1]^\top$. $F(\boldsymbol{\theta};\,\mathbf{p}_i)$ is the algebraic distance of a point $(x,\,y)$ to the conic $F(\boldsymbol{\theta};\,\mathbf{p})$.

Once all possible toes and central pads have been identified and defined by ellipses, they are stored in a local coordinate system database, where toes are ordered by angle.

Template Extraction

Next, an appropriate number of footprints of known species identification must be extracted to generate an initial template database. Members in this database are used subsequently for identifying unknown footprints. Templates must reflect the variance within species characteristics (e.g., age and sex) while also expressing the discerning characteristics among species. Tracks previously must have been independently correctly identified, such as by live-capturing individuals from the target species in the field and collecting footprints from them. The track acquisition process is manually aided by selecting appropriate footprint regions. From these cards, the k most representative ones are chosen for our template database, T.

A symmetric distance measure can be used to calculate correspondence between binary patterns (Klette and Zamperoni 1987). For fingerprint template selection, the minimum distance of unidentified prints from templates is used (Uludag et al. 2004), and this method has shown good experimental performance in dealing with intra-class variation. Based on these concepts, we use an adapted method for track recognition that calculates the average pairwise symmetric distance for a footprint with all other $n-1$ footprints.

The similarity between two sets is defined as the union (overlap) of nonintersecting parts:

$$A\Delta B = (A \cup B) - (A \cap B).$$

Based on this concept, a symmetric distance measure representing the similarity between two tracks A and B is calculated by normalizing the symmetric difference:

$$d(A,B) = \frac{\mathrm{card}(A\Delta B)}{\mathrm{card}(A \cup B)} \quad \text{where} \quad 0 \le d \le 1.$$

Here, d is a metric (see Klette and Zamperoni 1987, Klette and Rosenfeld 2004); thus it provides pairwise symmetric distances, and an average distance of a particular footprint i can be computed as follows:

$$\overline{d}_i = \frac{\sum \hat{d}_{i,j}}{(n-1)} \quad \text{for } i \neq j$$

where n is the number of footprints in the training set, and j is a footprint different from i.

Finally, all average distances are sorted by order, and the template set that contains the most representative templates is selected, based on a minimum average distance criteria.

This method endeavors to find the footprints that characterize maximum similarity with others in the training set and, therefore, that are good candidates to form the initial template database. Creating the template database is an important stage for accuracy. The number of templates in the database must be carefully determined. A large number of templates dramatically increases computing time for matching, whereas a small number might not be sufficient for robust identification. Generally the training data set must comprise the expected natural variation among tracks.

After initial template images are selected using the minimum distance method, further information about a particular template must be extracted from the original template image and stored in an XML database. The basic information that is manually extracted is characterized as follows: species, leg (i.e., left front, left hind, right front, and right hind), central pad area, the distances of toes relative to central pad, angles between each toe and its two neighbors, and area of toes.

Template Comparison

We are now able to compare unknown footprints from tracking cards with those in our template for automatic species identification. An algorithm seeks to find the most likely match by estimating similarity between potential unique footprint configurations and templates in the database. Because the central pad is more likely to leave clear marks on the tracking card, we start by finding all preliminary central pad ellipses based on area constraints (the area of a central pad must be within a specified range). All other ellipses that are close to the central pad (within a limited distance) will qualify as possible toes to that central pad. Unique footprints must now be defined and we develop a previous method for identifying these (Hasler et al. 2004). The central pad and all potential toes are placed into a local coordinate system where toes are ordered by angle, and all combinations of the central pad with these toes are iteratively compared with the template list. A similarity value is calculated for a potential combination (a central pad and its preliminary toes) and the selected template using a linear evaluation function. Here we introduce an automatic template database updating procedure, using an optimally weighted function that improves the evaluation response. To ensure high evaluation values for potential footprints that have small variations from the template, we replaced the linear function by a continuous Gauss function:

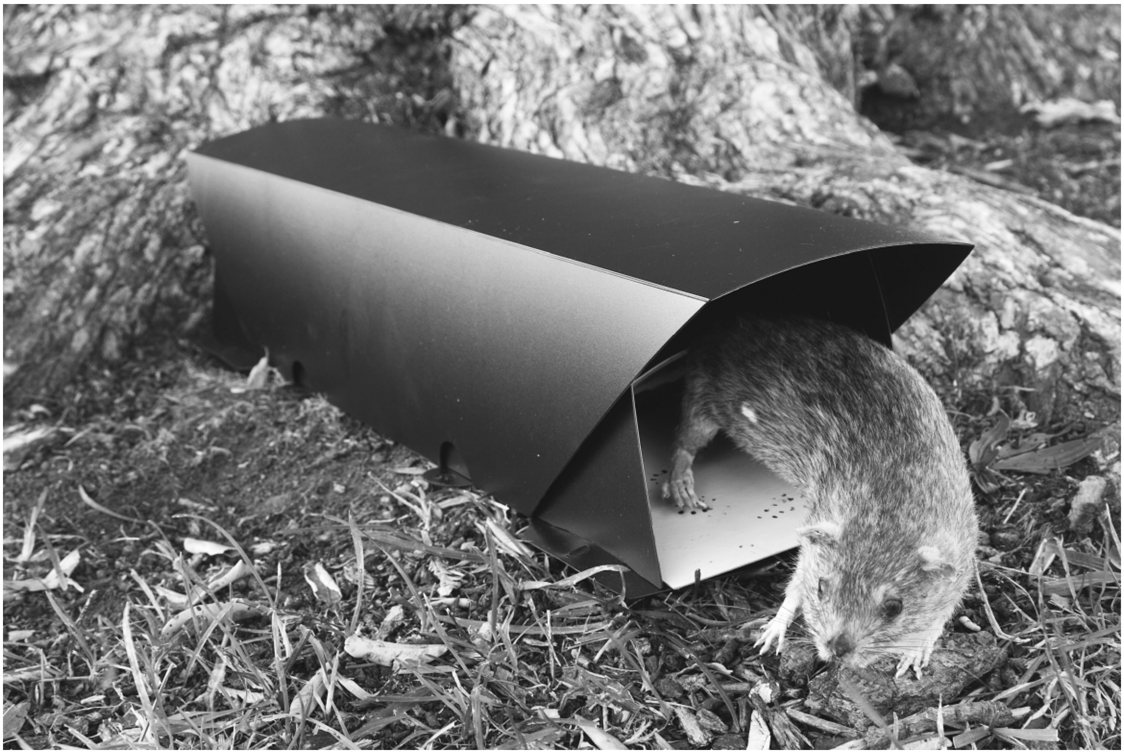

PLATE 1. Tracking tunnel with tracking card and Norway rat. Photo credit: J. Russell.

$$E_{h,r} = \exp\left[-(\alpha_{h,r} - \beta_{h,r})^2/\sigma_r^2\right]$$

where $E_{h,r}$ is the value of the evaluation function, $\alpha_{h,r}$ is the value of the hth potential toe for the rth parameter (distance, area, or angle), $\beta_{h,r}$ is the template value of an hth potential toe for the rth parameter, and σ_r is the template tolerance factor (or standard deviation) for the rth parameter. These are averaged across all h toes to give a normalized mean evaluation for each parameter r:

$$E_{\cdot r} = \frac{1}{n}\sum_{h=1}^{n} E_h$$

where n is the number of toes being evaluated. Each parameter r is then weighted and a final normalized evaluation value (in the range 0 to 1) can be calculated:

$$E_{\cdot\cdot} = \frac{1}{\sum c_r}\sum_{r=1}^{R} c_r E_r$$

where c_r is a weight value for each parameter r (initial values for all $c_r = 1$).

The similarity estimation function guarantees a higher output (greater value) for a comparable footprint with a template and a lower outcome (smaller value) for an incomparable sample. Track classification is now relatively straightforward. A threshold value is used to decide whether the preliminary footprint combination is a real footprint. Once the unknown footprint is confirmed, it will then be categorized to the same class as the comparable template. Software implementing the automatic track recognition method is *available online*.[5]

A constant template database is of limited use because it can become based upon an obsolete training set, and hence cannot incorporate new samples. We use dynamic template updating, which recycles previously identified unknown tracks and retrains them for our template database, where the retraining procedure is the same as for template extraction. Automatic template updating must be done with caution, however, because a biased template database will be generated if too many false samples are used for training, which will strongly influence the accuracy of our methodology. Only unambiguously identified samples above a certain identification threshold should be used for template updating.

DIFFICULT FOOTPRINTS

Faint footprints, footprints with missing toes, and merged prints all occur frequently on tracking cards (Fig. 3). These issues can be readily resolved, however. To detect faint tracks, the binarization method needs to be adapted. This is done by manually adjusting the tolerance to provide better regions, which will construct

[5] ⟨www.mi.auckland.ac.nz/ScanT⟩

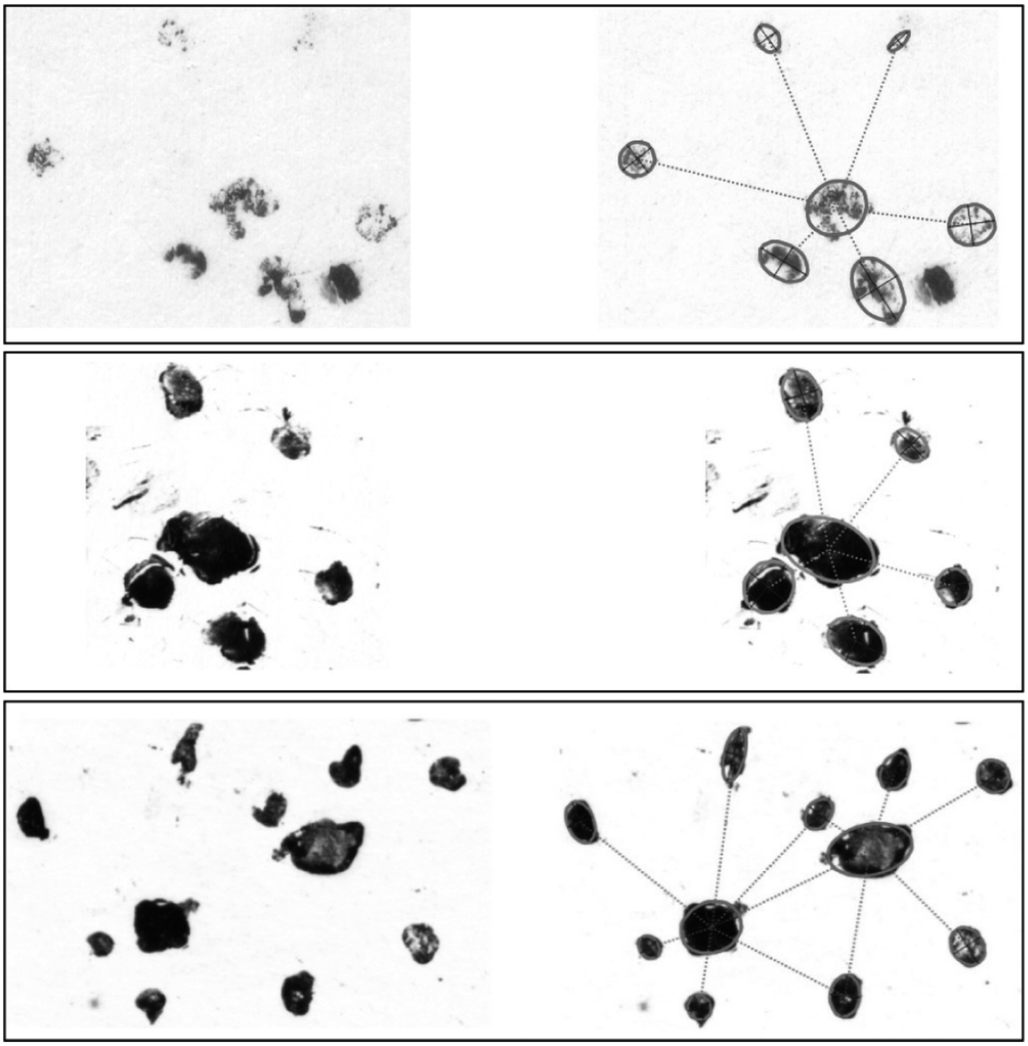

FIG. 3. (Top) Faint footprint. (Middle) Footprint with a missing toe. (Bottom) Two footprints with merged toes.

more accurate ellipses to represent toes or pads. For one or two missing toes, the algorithm automatically generates templates with missing toes during the similarity estimation process. In our implementation, templates in the database are automatically reformatted. For example, if m of n toes are missing, then each original template generates

$$\binom{n}{n-m}$$

new templates for each possible combination of missing toes. For overlapping prints, when the algorithm searches for the best match, toes can be shared by multiple footprints, provided that a central pad can only belong to one recognized footprint as such. If a central pad overlaps with a toe, then the pad is treated as a central pad for one and only one footprint and as a toe for all other footprints.

DEMONSTRATION

To demonstrate the method, we differentiate between three small-mammal species: the invasive rats *Rattus exulans*, *R. norvegicus*, and *R. rattus*, which co-occur on the New Zealand mainland and many islands (Russell and Clout 2004). A rat has four toes on the front foot and five on the hind foot. The front toes are evenly distributed and the hind central three toes are normally bunched and parallel. Rat footprints are approximately circular in shape, and if a line is connected between two end toes on the front or hind foot, the line bisects or lies behind the central pad (Russell et al. 2008). Rat tracks are relatively different because of species characteristics, but manual species identification is confounded by large variation among populations, individual ages (size), and possibly the sex of individuals relative to subtle differences among species (e.g., Golding and Harper

Table 1. Classification results for individual footprints and tracking cards for three species of *Rattus*.

Classification	Percentage of footprints		
	R. exulans (29 cards, 164 prints)	*R. norvegicus* (12 cards, 51 prints)	*R. rattus* (32 cards, 134 prints)
True positive (sensitivity)	70.1	78.4	76.1
True negative (specificity)	90.8	90.1	90.0
False positive (α)	9.2	9.9	10.0
False negative (β)	20.7	17.6	18.7
Did not detect print	9.1	3.9	5.2
Identified	86.2	83.3	84.4
Unidentified	13.8	16.7	15.6

Notes: Correctly assigned footprints are denoted as "true positive" and "true negative," incorrectly assigned footprints as "false positive" and "false negative," and undetected footprints as "did not detect print." If a majority of footprints on a tracking card are correctly classified, it is considered "identified"; otherwise it is "unidentified."

2008). Therefore, distinguishing tracks of different species is difficult (e.g., Fig. 1). Digitized tracks of rats previously have been analyzed for defining a sciatic functional index, SFI (de Medinaceli et al. 1984, Lowdon et al. 1988), using stride length, footprint length, and toe spread for diagnosing experimental injuries in individual rats. However, our motivation differs from analyzing individual rats instead focusing on identifying species-level characteristics for ecological applications.

Rat tracks were collected from around New Zealand using tracking tunnels and pre-inked tracking cards (Connovations, Auckland, New Zealand; see Plate 1). Tracks were acquired from offshore islands where only one species was present, thus ground-truthing species identification on any particular card for our template database and demonstration. Following digital track acquisition, 75% of 97 footprints from all three species were identified as suitable for the template training set. These templates were then applied to an independent testing set consisting of a combination of 349 footprints of all three species from 73 other tracking cards. In addition, we dynamically updated our template database based on the criterion unique to rat footprints that, if a line segment is drawn between the two end toes of a rat footprint, the line must bisect, or lie behind, the central pad. This property was a good candidate for stabilizing templates. Thus two conditions were applied to restrict the template updating procedure: a high similarity value, and this line segment constraint.

Over 70% of footprints among the three invasive rat species were correctly identified ("true positive"), and over 83% of tracking cards were correctly classified (Table 1). Results were consistent across species. Type I and II error rates were appropriate at around 0.10 and 0.20, respectively, whereas only $<10\%$ of footprints were not detected at all by our image recognition algorithm. This result was obtained with around 100 template database footprints, which we recommend as a suitable rule-of-thumb minimum. However, for other species the minimum number of footprints required will vary relative to the number of cryptic species in the community, and their within- and among-species footprint variability. Testing footprints were kept in their original conditions without preprocessing, so that a number of them contained uncertain prints (e.g., faint and smudged prints). These uncertainties impacted on individual footprint recognition rates, but they did not greatly affect overall recognition percentages for tracking cards. The majority of prints on tracking cards were correctly identified by our algorithm, and satisfactory results were derived for all species, even though tracks came from an unknown number of individuals. The true positive rate could have been improved by increasing the number of templates, but at a cost of computational time. An important result was derived for one tracking card that successfully identified a solitary *R. norvegicus* invader on a small rat-free island in New Zealand, which previously had been identified only through much more costly genetic fingerprinting (see Russell et al. 2005).

Discussion

Developing accurate methods to identify low-density or cryptic species is vital for wildlife research and monitoring (Whisson et al. 2005, Watts et al. 2008). Animal tracks can be readily collected, but the requirement of expert skills and the subjective nature of manual identification are problematic (Gaston and O'Neill 2004). We have described and demonstrated an automatic track recognition method that can be used to differentiate between footprints of similar small-mammal species. The template-matching method is only limited by the quality and quantity of template tracks. Computational time for a single card on a Core2 Duo 3.0GHz computer with 2.0GB of RAM is ~5–10 seconds. With changes to the track acquisition method, other taxa such as reptiles (Siyam 2006) and insects

(Hasler et al. 2004) also could be automatically recognized. The method could complement other passive detection tools such as hair-tube tunnels for DNA analysis (Lindenmayer et al. 1999). With larger template databases, identification below species level may become possible, such as differentiating between sexes, age classes, or even individuals. Such applications would require significant dimorphism between groups, however (i.e., greater variability between, rather than within, groups).

Automatic track recognition would have important applications for detecting individuals at low density where other detection methods struggle, and where detection may be confounded by other morphologically similar species (Lindenmayer et al. 1999). Invasive rat species are an ongoing problem in New Zealand and elsewhere (Russell et al. 2008). We successfully identified the footprints of different species of invasive rats, which has important applications to island biosecurity. Knowledge of the species of invading rat affects how conservation managers respond to island invasions, due to subtle behavioral differences between the species (O'Connor and Eason 2000, Russell et al. 2008).

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