Understanding Tracks of Different Species of Rats

Guannan Yuan[1], James Russell[2,3], Reinhard Klette[1],
Bodo Rosenhahn[1], and Steven Stones-Havas[1]

[1]CITR, Computer Vision Unit, Department of Computer Science
[2]Ecology and Animal Behaviour Research Group, School of Biological Science
[3]Statistical Ecology and Bioinformatics Research Group, Department of Statistics
The University of Auckland

Abstract

Recognition of animal tracks plays an important role in environmental research and pest control. So far such track analysis can only be accurately carried out by experienced biologists. In this paper we discuss the potential of image analysis methodologies for allowing automatic identification of rat tracks. The approach is basically a refinement of template matching (as designed earlier for automated track localization), now also allowing identification of rat species.

Keywords: rat tracks, footprint recognition, template matching

1 Introduction

Three species of rats are used as study samples in our project; the ship rat (*Rattus rattus*), Norway rat (*R. norvegicus*) and Pacific rat (kiore, *R. exulans*). Their tracks are collected by a tracking system which involves a tracking tunnel, a pre-inked tracking card and lures placed on the centre of the card. Animals attracted by lures walk through the tracking tunnel and leave their footprints on the tracking card. Tracking cards are then scanned at different resolutions, and resulting digital images are automatically analyzed.

Three species of rodents have caused species extinctions and devastated native biota across the world [1]. All three species of invasive rats were introduced to New Zealand when humans first visited the main islands [7]. Around the 10th century the smaller Pacific rat was brought to the mainland by Maori settlers. In the 18th century the larger Norway rat arrived in New Zealand with European or North American sailing ships. The intermediately sized ship rat was probably introduced to the mainland in the early 19th century and is now the most common and dominant rat. All three rats persist on offshore islands where they continue to diminish conservation efforts [13].

The Wistar rat is a common strain of white lab rat (domesticated wild Norway rat) for medical or biological experimental purposes [12].

To recognize these rats, some major biological differences among their bodies are described in Table 1, see [8]. Wistar rat is also listed as an individual case in Table 1 because, after long term domestication, the Wistar rat has some evolutions compared with the wild Norway rat. Rat tracks are relatively different because of species characteristics. Therefore, experts are able to subjectively identify different species using their footprints.

However, distinguishing tracks is difficult for inexperienced people because of the similarities between different rat tracks. Figure 1 shows two left front prints of a kiore and a ship rat; the footprint of this ship rat is slightly larger than kiore. More detailed features (e.g., the severity of experimental injuries to a rat) can also be derived from a track, see, e.g., [11] for early studies.

A rat has four (five) toes on the front (hind) foot. The front toes are evenly distributed and hind central three toes are normally bunched and parallel [2]. Rat footprints are fairly circular in shape,

Norway rat	Ship rat	Kiore	Wistar rat
Max. HBL	(*head-body*	*length)*	(mm)
250	225	180	283
Adult	*weight*	(g)	
200-300	120-160	60-80	200-485
Hind	*foot*	*length*	(mm)
30-41.5	28-38	24.5-31	over 30
Tail			
Shorter than HBL	Longer than HBL	About same as HBL	Shorter than HBL
Back	*color*		
Brown	Grey-brown or black	Brown	White

Table 1: Comparison of rat species.

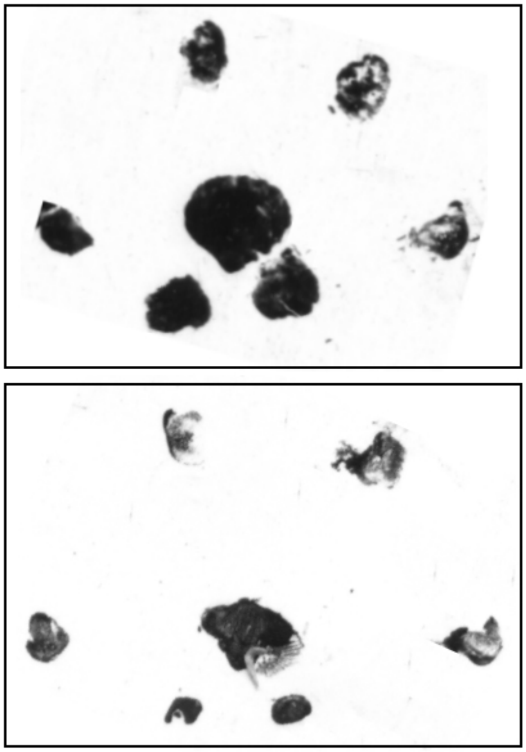

Figure 1: Left front prints of kiore and ship rat.

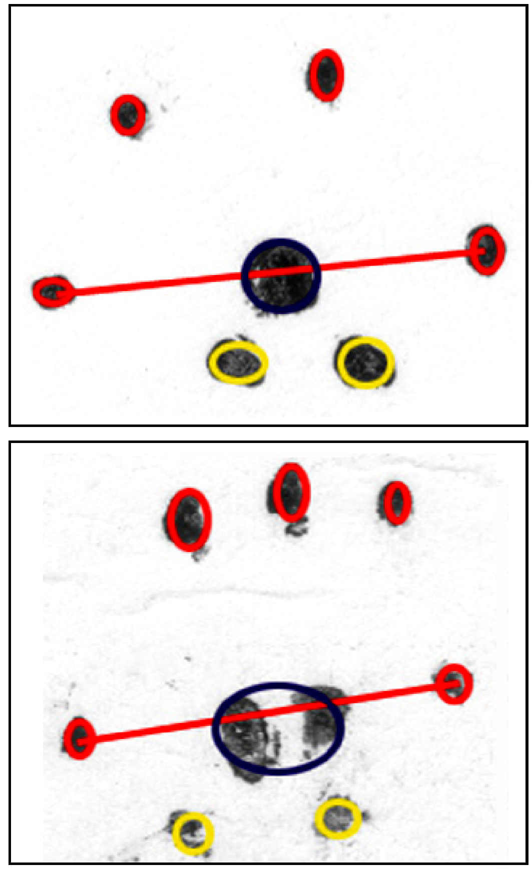

Figure 2: A front foot and a hind foot of a ship rat: red ellipses represent toes; blue ellipses represent cental pads; yellow ellipses represent lumps (see online version of repot for colors).

and if a line is connected between two end toes on the front or hind foot, the line should bisect or lie behind the central pad [5]; see Figure 2.

Tracks of rats on X-ray film have been analyzed in [3], discussing the use (for diagnosing an individual rat) of stride length, foot print length, and toe spread for defining a sciatic functional index (SFI). [11] followed this work, and the quantitative analysis of locomotion of rats is a common subject today in biomedical research.

Our motivation (i.e., classification of rat species) differs from analyzing individual rats. This paper is an extension of [6]. Here footprints of mice and rats were discriminated using template matching. This method first created a universal template for rodents, and then followed these steps:

(i) a common binarization method for image segmentation, then (ii) ellipse fitting for identifying toes and pads, and finally (iii) apply a linear evolution function for template matching.

The experimental results of this work showed that template matching might be a suitable way to distinguish small animal tracks.

Because the previous method had only one universal template for all rats and mice, distinguishing different species was impossible. This paper intends to discriminate tracks of different rat species using image processing algorithms and pattern recognition techniques.

Most algorithms from [6] have been modified to guarantee better performance (e.g., better pattern recovery using new binarization and ellipse fitting algorithms).

For a wider application, the new methodology is able to deal with some "difficulties", such as footprints with missing toes or faint footprints.

2 Approach and methodology

An automatic track recognition system is concerned with the following main stages:

(i) *track acquisition* (i.e., acquire footprint images and determine their formats for further analysis), (ii) *footprint template extraction* (i.e., extract an initial template database from a given training set for future matching), (iii) *template matching* [i.e., combine *track identification* for querying a template database to find a comparable template, for example based on *similarity estimation* (between unknown footprints and templates), and *track classification* for classifying inputs into different classes according to their geometric characteristics], and (iv) *template updating* (i.e., update template database dynamically, improve algorithm efficiency).

2.1 Track acquisition

Rat tracks are collected from around New Zealand using tracking tunnels. Most are acquired from islands where only one rat species is present hence guaranteeing the species. Using tracking tunnels, baits and tracking cards to non-invasively capture small animal tracks is widely recognized as a suitable method of indirect population study. To provide computer analyzable footprint patterns, tracking cards are scanned at 300 and 600dpi using flatbed scanners and stored in 'bmp' format as gray-scale pictures. Generally, the dimension of a 300dpi scanned tracking card is about 1170×3500 pixels, and occupies around 3.9 Megabytes of memory space.

For purposes of template extraction and experimental evaluation, any unknown tracking cards are pre-classified by experienced biologists. Some cards are then selected as a training set for template extraction while others become the test set for experimental purposes.

As tracks are randomly collected from the field, most are not clear. This requires that our methodology should have greater tolerance, which is necessary for it to have application to wildlife biologists.

2.2 Footprint template extraction

The first stage of the methodology is to generate an initial template database, which can provide templates for further comparison. The principle of template selection is to elect multiple templates that can reflect the variance and represent the mainstream of a given training set. The number of templates in the database also needs to be carefully determined. A large number of templates will dramatically increase computation complexity, while a small number might not be sufficient.

In [15], a method (MDIST) was introduced to perform fingerprint template selection. It showed good experimental performance to deal with intra-class variation. In [9], a method using a symmetric distance to measure correspondence between binary patterns was given. Based on these concepts, an adapted method with regard to footprint recognition is proposed as follows:

(i) calculate pair-wise symmetric distance between n footprints in the training set; (ii) for each footprint, find its average symmetric distance with respect to all other $n-1$ footprints; (iii) create a template set using minimum distance criteria to choose k templates.

Similarity measurement between two footprints is based on symmetric difference, which is defined as the union of nonintersecting parts between two sets:

$$A \Delta B = (A \cup B) \backslash (A \cap B)$$

The symmetric difference allows to define a metric which represents the similarity between two footprints by normalizing the symmetric difference:

$$d(A,B) = \frac{\mathrm{card}(A \Delta B)}{\mathrm{card}(A \cup B)} \qquad 0 \leq d \leq 1$$

d is a metric (see [9, 10]); thus it provides pair-wise symmetric distances, and an average distance of a particular footprint i can be computed as follows:

$$a_i = \frac{\sum d_{i,j}}{(n-1)} \qquad i \neq j$$

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 a template set T, which has k templates, will be selected based on minimum average distance criteria.

This method is endeavoring to find a number of footprints which represent maximum similarity with others in the training set, and therefore, they are good candidates to form the initial template database.

After initial templates are selected, important information about a particular template should be extracted from the original template image and stored in an XML database.

Basic information that is extracted is described as follows: rat species, foot 'corner' (i.e., left front, left hind, right front and right hind), central pad area, distances of toes relative to central pad, angles between each toe and its two neighbors, and area of toes.

2.3 Template matching

The principle of template matching is to compare the potential footprints on a tracking card with all templates in the database, and seek the most likely match. Two sub-steps are inclusive, namely track identification and classification. In track identification, the algorithm searches all templates and estimates similarities to find the most likely template, before deciding the matching footprint and hence species.

2.3.1 Track identification

To identify a footprint on a new tracking card, the procedure is divided into three sub-steps: segmentation, footprint ellipse fitting (all possible toes, lumps and central pads), and similarity estimation between potential footprint and templates in the database.

Binarization and segmentation

Binarization is the first stage to render explicit footprint patterns on a tracking card. Since the intensity of a rat footprint greatly depends on ink quantity on its pads, a fixed binarization threshold cannot reduce noise or detect footprint patterns reasonably. [16] compared binarization methods and identified Abutaleb's method as the most reliable for binarizing insect footprints. In case of rat footprints, large variances in mean values of individual prints (on the same card) made a straightforward adaptation of Abutaleb's method impossible.

We decided for an adaptive binarization method. We map a gray level image f into a two-level image h as follows: apply a standard scan on f; as long as sliding mean and pixel value are within a defined (small) range, we continue with scanning f, otherwise we initiate a region A (i.e., a connected set of pixels p) in input image f; A "grows" (unfortunately, dependent upon scan order of pixels) as a maximum-size component of pixels all satisfying

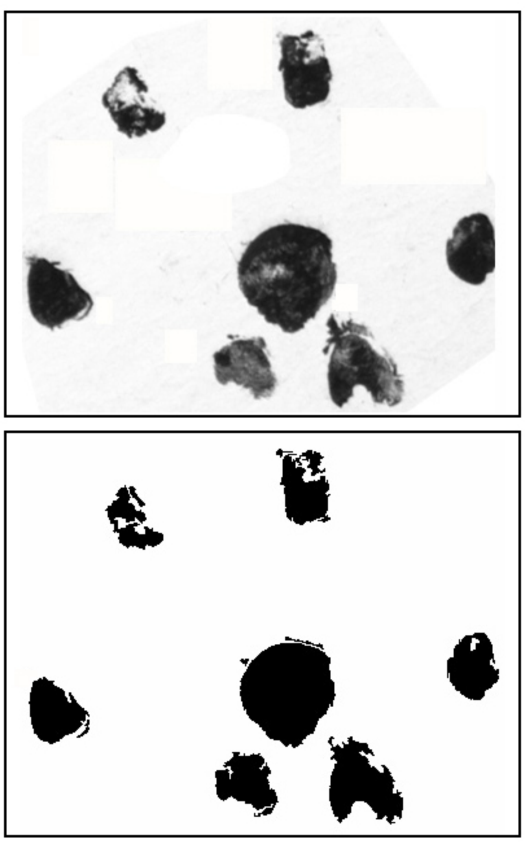

Figure 3: Top: original image. Bottom: the adaptive binarization result for $t_A = 32$ (for any region A).

$$|m_{A,p} - f(p)| \leq t_A$$

where $f(p)$ is the image value at pixel p, t_A is the intensity tolerance for this region (e.g., defined by a percentage of the initiating pixel value) and $m_{A,p}$ is the sliding mean of region A (up to reading pixel p). It follows that all pixels q adjacent to region A satisfy

$$|m_{A,q} - f(p)| > t_A$$

$h(p)$ is the final binarization response for all pixels $p \in A$, with

$$h(p) = \begin{cases} 255 & \text{if } m \leq card(A) \leq M \\ 0 & \text{otherwise} \end{cases}$$

where $m < M$ are thresholds for tolerable sizes of regions A; $h(p) = 0$ for pixel p which is not in such a region A.

Regions A with value 255 are treated as potential parts of footprint patterns for further analysis (Figure 3).

In many cases, drag marks cause that footprint patterns (e.g., central pad and lumps) are connected, and these marks normally have obviously lower intensity values than real print patterns. Binarization can wipe off such drag marks and other noises. Therefore it ensures better footprint patterns for future analysis.

Footprint ellipse fitting

Next we identify all possible toes and central pads in the binarized image h, which are fairly circular in shape. Binarization provides potential pad marks; these marks are (connected) regions. Pixels $p = (x, y)$ on the border of each of those regions are used for a least square fit of a uniquely defined ellipse. We use the direct least-square fitting algorithm of [4], and give a brief review of this method:

A generic conic can be represented as:

$$F(\alpha, x) \quad = \quad ax^2 + bxy + cy^2 + dx + ey + f$$

One method to fit a conic is to minimize the algebraic distance $F(\alpha, p_i) = d$ of all n border points p_i in the least squares sense, formally represented as follows:

$$\hat{\alpha} \quad = \quad argmin_\alpha \left\{ \sum_{i=1}^{n} F(\alpha, p_i)^2 \right\}$$

The minimization problem can be solved by a rank-deficient generalized eigenvalue system; eigenvalues λ are defined by

$$D^T D\alpha = S\alpha = \lambda C\alpha$$

for a *design matrix* D, a *scatter matrix* S and a *constraint matrix* C, which are defined as follows:

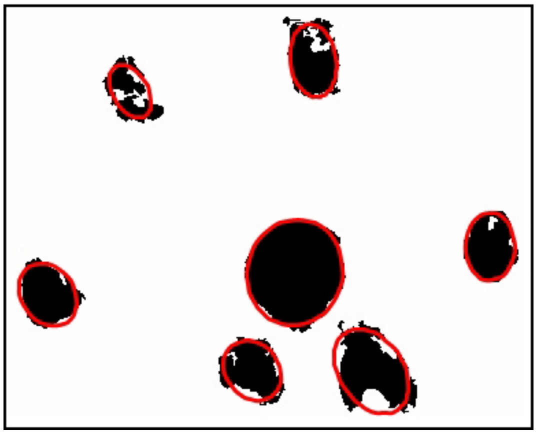

Figure 4: Fitted ellipses for the binary image of Figure 3.

$$
\begin{aligned}
D &= [\vec{p_1}, \vec{p_2}, \cdots, \vec{p_n}]^T \\
S &= D^T D \\
C &= \begin{bmatrix} 0 & 0 & -2 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ -2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\end{aligned}
$$

A resulting ellipse is guaranteed by this algorithm. See Figure 4 for an example.

Similarity estimation

Once we have all possible toes and central pads after ellipse fitting, the next main task is to evaluate the similarity between a potential footprint configuration and a template in the database. Since the central pad is more likely to leave clear marks on the tracking card, we start to find 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 be qualified as possible toes to that central pad.

A method was proposed in [6] to search for the best combinations of toes for a specific central pad. The central pad and its preliminary 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 will be calculated for the given combination (a central pad and its preliminary toes) and the selected template. A liner evaluation function was used in [6]. To ensure a high evaluation value for a potential footprint which only has minor differences to a template, we replaced the linear function by a continuous Gaussian function

$$E_i = e^{\frac{-(a_i - m_i)^2}{\sigma^2}}$$

where E_i is the evaluation of a particular parameter value (distance, area, angles) of a preliminary toe i, a_i is the parameter value for this toe, m_i is the parameter value of the template, and σ is the tolerance factor (or standard deviation) for this parameter. Therefore, a normalized evaluation for each parameter k is defined as follows:

$$E_k = \frac{1}{n} \sum_{i=1}^{n} E_i$$

Where n is the number of toes. Finally, a normalized evaluation value (in the range 0 to 1) can be calculated as below:

$$E = \frac{1}{\sum C_k} \sum_{k=1}^{K} C_k E_k$$

where C_k is a weight value for each parameter (initial value C_k=1).

2.3.2 Track classification

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 then straightforward. A threshold value is used to decide whether the preliminary footprint combination is a real footprint. Once the potential footprint is confirmed, it will then be categorized to the same class of the comparable template.

2.4 Template updating

A constant template database is of limited use because it comes from an obsolete training set, and hence can not incorporate new samples. We also use dynamic template updating, where the basic idea is to reuse already recognized tracks to retrain them in our template database, where the retraining procedure is the same as template selection. However, template updating should be carefully managed because, if too many false samples are used for training, it will generate a biased template database, and therefore influences the accuracy of our methodology. Therefore, only highly confirmed samples will be chosen for template updating.

The first section mentioned a remarkable biological characteristic of rat footprints: if a line segment is drawn between two end toes of the rat footprint, the line must bisect, or lie behind of the central pad. This property might be a good candidate to stabilize templates. Therefore, two conditions are applied to restrict the template updating procedure, the first is a high similarity value, and the second is this line segment constraint.

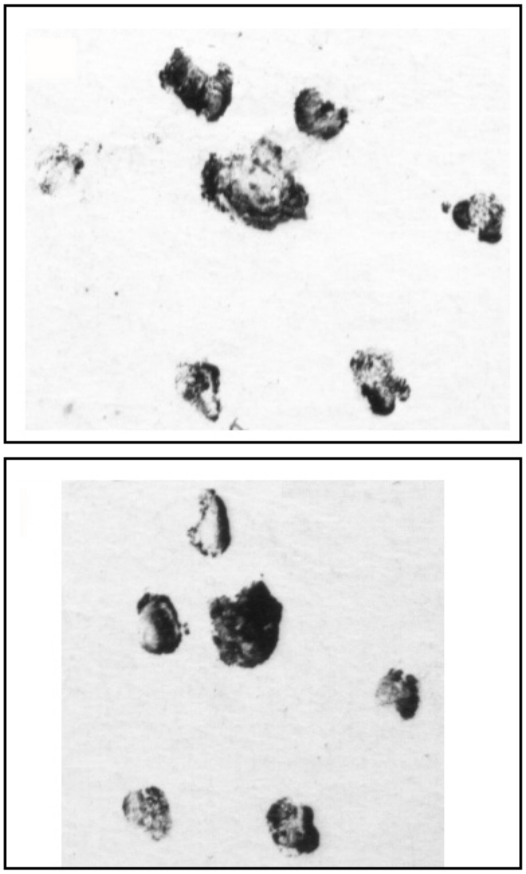

Figure 5: Top: faint footprint. Bottom: footprint with a missing toe.

3 Problems to be addressed

Faint footprints and footprints with missing toes are two frequently occurring situations on tracking cards, see Figure 5. Here, we proposed two methods which can help to address these problems.

Our adaptive binarization method allows detection of faint tracks. Adjusting tolerance t_A properly can provide better regions, and these regions construct more accurate ellipses to represent toes or pads.

A few toes (one or two) missing should still be acceptable. We generated templates with missing toe(s) to fix this problem. In our implementation, templates in the database are automatically reformatted. For example, if "one toe (or lump) is missing" is acceptable, then each original template will generate six new templates for a front foot and seven for a hind foot.

4 Experimental results

We illustrate experimental results for a four-class situation: footprints of kiore, Norway, ship and Wistar rats. Table 2 shows the number of used training footprints and templates in the data base, generated by using these footprints. For each item, the first number shows the size of the training set, and the second is the number of templates. For example, using the template generation algorithm, 30 templates are generated for ship rats (using 42 footprints). These templates were then applied to a testing set (which contains 373 footprints from our 81 testing tracking cards) to identify footprints of all species.

	Kiore	Norway	Ship	Wistar
Front left	8(6)	5(4)	14(9)	11(6)
Front right	12(8)	7(5)	12(8)	3(3)
Hind left	7(5)	4(4)	6(6)	5(3)
Hind right	9(6)	3(3)	10(7)	3(2)
Total	36(25)	19(16)	42(30)	22(14)

Table 2: Templates of kiore, Norway rat, ship and Wistar rat.

	Kiore	Norway	Ship	Wistar
Total prints	164	45	134	30
True positive	115	34	102	25
False positive	34	9	25	2
True negative	15	2	7	3

Table 3: Classification results of individual footprints.

	Kiore	Norway	Ship	Wistar
Total cards	30	10	32	9
Identified	25	8	27	8
Unidentified	5	2	5	1

Table 4: Classification results of tracking cards.

The experimental results of individual footprints are shown in Table 3. We denote correctly recognized footprints as "true positive", wrongly recognized footprints as "false positive", and missed footprints as "true negative".

If the majority of footprints on a tracking card is correctly classified, the card is then marked as "identified", otherwise "unidentified". Experimental results of tracking cards are given in Table 4.

In our experiments, see Figure 6, over 70% footprints of all species are correctly classified, and all have over 80% tracking card recognition rate. All test footprints are from original cards, and a number of them are faint, merged or smudgily prints. Although these uncertain prints impact on footprint recognition rate, our algorithm still can distinguish the majority prints on tracking cards and identify most tracking cards correctly. The used Wistar rat tracks came from four individuals and obtained in laboratory condition, and thus fewer templates were used

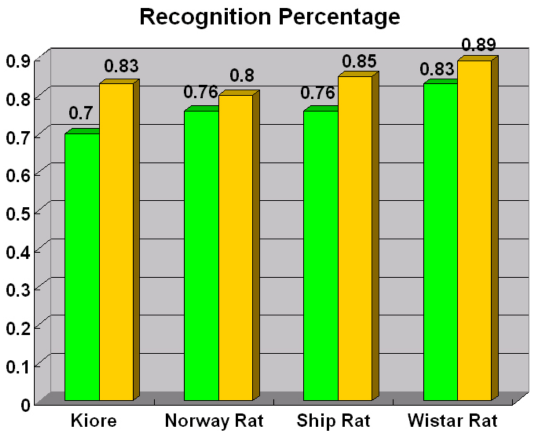

Figure 6: Recognition percentage of different species. Green columns represent footprint recognition rate, and yellow columns are tracking card recognition rate.

which still allowed highest recognition rates; tracks of other rats came from a much larger (actually unknown) number of individuals, and hence more templates were needed. Alternatively, it is possible to improve the true positive rate by increasing the template number. However, there is a tradeoff between number of templates and computation time. A remarkable result was derived from our experiments, an important tracking card of Norway rat was rightly classified and verified as it detected a Norway rat invasion on a small island in New Zealand (previously also already identified by experts).

5 Conclusion

Invasion by all three rat species is an ongoing problem in New Zealand [14]. Developing accurate methods to identify rat tracks and species would be beneficial to conservation managers. However, the lack of experts and the subjective nature of this method (identification by foot prints) is a problem. Generating larger sets of tracking cards under controlled conditions would help to overcome this situation.

The proposed methodology might not be limited to identification of rat tracks. Understanding other small animal tracks is also possible through adding more corresponding templates, and therefore, this could become a general method for small animal track recognition.

Acknowledgements The authors thank Kevin Parker, Institute of Natural Resources, Massey University, for providing kiore tracks. Shandong University, for providing Wistar tracks, and Xiaopeng Guo for her cooperation in collecting Wistar prints.

References

[1] I. A. E. Atkinson. The spread of commensal species of *Rattus* to oceanic islands and their effects on island avifauna. In *Conservation of Island Birds* (P. J. Moors, editor), Int. Council Bird Preservation Tech. Publ., **3**:35–81, 1985.

[2] Common rat. *http://www.skullsite.co.uk/Prints/Rat/rat.htm* (last access: 03/05/2005).

[3] I. de Medinaceli, E. De Renzo, and R. J. Wyatt. Rat sciatic functional index data management system with digitized input. *Comput. Biomed. Res.*, **17**:184–192, 1984.

[4] A. W. Fitzgibbon, M. Pilu, and R. Fisher. Direct least-squares fitting of ellipses. *IEEE Trans. Pattern Analysis Machine Intelligence*, **21**:476–480, 1999.

[5] C. Gillies and D. Williams. A short guide for identifying footprints on tracking tunnel papers. Department of Conservation, New Zealand (unpublished report).

[6] N. Hasler, R. Klette, B. Rosenhahn, and W. Agnew. Footprint recognition of rodents and insects. In Proc.*Image Vision Computing New Zealand*, pages 167–172, 2004.

[7] R. N. Holdaway. Arrival of rats in New Zealand. *Nature*, **384**:225–226, 1996.

[8] C. M. King, editor. *The Handbook of New Zealand Mammals*, Second Edition. Oxford University Press, Auckland, 2005.

[9] R. Klette and P. Zamperoni. Measures of correspondence between binary patterns. *Image Vision Computing*, **5**:287–295, 1987.

[10] R. Klette and A. Rosenfeld. *Digital Geometry - Geometric Methods for Digital Picture Analysis.* Morgan Kaufmann, San Francisco, 2004.

[11] I. M. R. Lowdon, A. V. Seaber, and J. R. Urbaniak. An improved method of recording rat tracks for measurement of the sciatic functional index of de Medinaceli. *J. Neuroscience Methods*, **24**:279–281, 1988.

[12] Rat Species, Strains, Breeds and Varieties. *http://www.ratbehavior.org/RatSpecies.htm* (last access: 15/08/2005).

[13] J. C. Russell and M. N. Clout. Modelling the distribution and interaction of introduced rodents on New Zealand offshore islands. *Global Ecology & Biogeography*, **13**:497–507, 2004.

[14] J. C. Russell and M. N. Clout. Rodent incursions on New Zealand islands. In Proc. *Australasian Vertebrate Pest Conference*, pages 324–330, Landcare Research, 2005.

[15] U. Uludag, A. Ross, and A. Jain. Biometric template selection and update: a case study in fingerprints. *Pattern Recognition*, **37**:1533–1542, 2004.

[16] Y. W. Woo. Performance evaluation of binarizations of scanned insect footprints. In Proc. *Combinatorial Image Analysis*, LNCS 3322, pages 669–678, Springer, Berlin, 2004.