ICIC Express Letters
Part B: Applications
Volume **13**, Number **9**, September **2022**
ICIC International ©2022 ISSN 2185-2766
pp. **915–921**

DISCRIMINATION OF ANIMALS IN JAPAN BY MACHINE LEARNING USING FOOTPRINT IMAGES

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Received March 2022; accepted June 2022

Abstract. *The distributions of various animal species have been surveyed for natural conservation, natural development, and biological research. In this study, we developed a method to discriminate between animal species based on the shape and size of footprint images. We propose a machine learning-based classification method to discriminate among footprint images of nine species of animals, including Procyon lotor, Mustela itachi, Cervus nippon yesoensis, Nyctereutes procynoides albus, Ursus arctos yesoensis, Lepus timidus ainu, Sciurus vulgaris orientis, Vulpes vulpes schrencki, and Martes melampus. We present the results of experiments showing that the proposed grouping was able to efficiently and effectively distinguish images of footprints of the nine species and the proposed convolutional neural network (CNN) model was able to classify nine species with an average accuracy of 94.5%.*
Keywords: Footprint, Animal, Image processing, CNN

1. **Introduction.** Surveys of the distributions of wild animals have been conducted for natural conservation, development, and biological research. For example, behavioral analysis was performed using GPS data collected from devices attached to Falco amurensis [1], and researches on animal identification and behavior recognition have been conducted using video data [2]. Animal classification has also been performed from camera-trap images [3]. Recently, optimization algorithms were proposed for the use of UAVs to track individual Ovis aries [4]. In addition, digital data acquired through remote sensing have been used to identify animals based on patterns of herd behavior [5]. In particular, this approach has been used to detect Ursus maritimus, which is widely and sparsely distributed [6]. However, in these methods, data are acquired directly from wild animals; therefore, the detection systems need to operate continuously during the animal's typical hours of activity.

In contrast, data can also be acquired from trace evidence left by wild animals, such as footprints, which remain at a location for some period of time; therefore, the distribution need not always consider the activity period of wild animals. Hence, species identification and insight into the activities of animals from footprint traces can contribute to reductions

DOI: 10.24507/icicelb.13.09.915

in the cost of data acquisition efforts. A method was proposed to identify species using their stride length from images of footprints captured by airborne remote sensing systems [7]. However, the low resolution of the images was insufficient to discriminate the species based on the shape and size of footprints.

Therefore, in this study, we developed a method to discriminate animal species based on the shape and size of footprints, regardless of whether the images were collected during day or night. In a previous study [8], we proposed a feature extraction method for species discrimination using footprint images of Procyon lotor and Nyctereutes procynoides albus in Hokkaido, Japan. The proposed method was able to extract the footprint area left on soil and snow to classify Procyon lotor and Nyctereutes procynoides albus with an average accuracy of 87.5%. These results suggest that the features of footprint images are useful for species discrimination in animals. In this study, we propose a method of species discrimination for animals using a convolutional neural network (CNN) model, which we trained to distinguish nine species of animals. We present the results of experiments with the proposed method, which show that the model obtained an average accuracy of 94.5% in the classification of nine species of animals.

The remainder of this study is summarized as follows. The background and purpose of this study are described in Section 1. In Section 2, the target animals, their footprints, and the data used in the experiment are described. In Section 3, we explain the procedures used to analyze the data. In Section 4, we present the results of the analysis, and discuss the usefulness of the proposed method. Section 5 concludes the work and suggests some possible directions for future research.

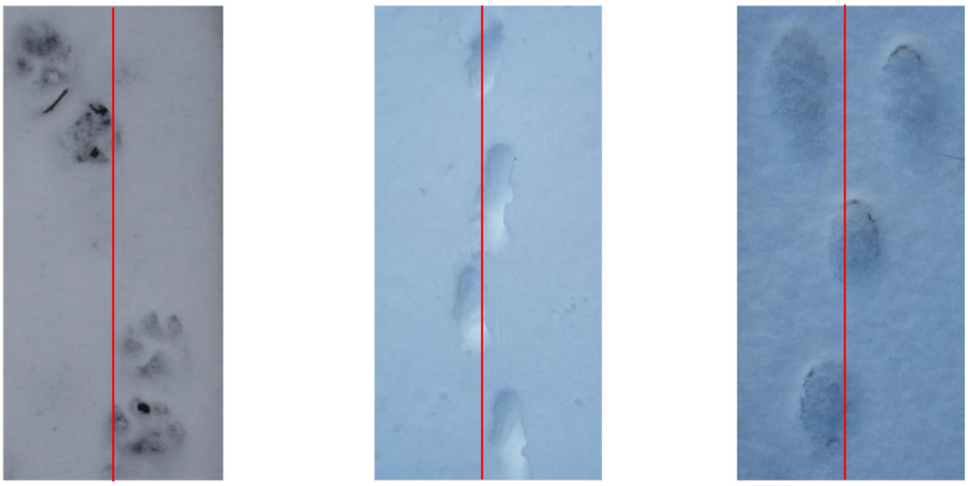
2. **Target Animals and Data Used.** In this study, we examined footprint images acquired in Japan, which comprised images of animal tracks. The data included 30 samples of Procyon lotor, 7 of Mustela itachi, 16 of Cervus nippon yesoensis, 32 of Nyctereutes procynoides albus, 7 of Ursus arctos yesoensis, 9 of Lepus timidus ainu, 9 of Sciurus vulgaris orientis, 7 from Vulpes vulpes schrencki, and 5 samples of tracks from Martes melampus.

These animal footprint images included two main features, the first being uncertainty as to the environment in which the photos were taken. For example, the footprint images could be roughly divided in terms of ground conditions into those imprinted in snow and those imprinted in soil. The second is the difference in footprints between species of animals. For example, the shapes of footprints exhibit significant morphological differences between species, such as the shapes and sizes of their digits and palms, as shown in Figure 1. In addition, continuous footprints are imprinted in various shapes depending on the species. As shown in Figure 2, the dataset included cases in which two footprints were left on each side, cases in which both were left in a straight line, and cases in which both footprints of an animal's hind legs were left side by side.

Some finger- and palmprints
(Procyon lotor)

Hoofprints
(Cervus nippon yesoensis)

FIGURE 1. Examples of the footprints of different species



Two footprints on each side (Nyctereutes procynoides albus) | Footprints in a straight line (Vulpes vulpes schrencki) | Both footprints of hind legs side by side (Lepus timidus ainu)

Figure 2. Example of how footprints left differ depending on the walking style

3. **Proposed Method.** The proposed footprint discrimination method involves grouping and preprocessing the data and subsequently performing discrimination using a CNN model.

3.1. **Grouping.** To distinguish animals efficiently, we hierarchically grouped similar types of features found in footprint images. The results of grouping the footprint images constituted prior information during processing.

In footprint photography acquired by an operator, there are typically cases in which a single footprint is imaged at a short distance and cases in which a continuous series of footprints are imaged at a longer distance. In this study, we grouped the images according to these two cases.

3.1.1. *Grouping of footprints recorded at a short distance.* Footprints imaged at short distances were clearly visualized; therefore, classification was performed based on differences in the shape of footprints. The classification procedure is illustrated in Figure 3. First, the footprints in soil and snow images were classified based on the differences in the ground conditions of the images. Next, focusing on the differences in the shapes of the footprint images, the soil and snow images were classified as round in soil images (Group A1), hoof (Group B1), round in snow images (Group C), and butterfly and Y-shaped (Group D) footprints. The results of the group classification for the nine species of animals are summarized in Table 1.

3.1.2. *Grouping of footprints recorded at a long distance.* Images taken from long distances typically show a continuous series or trail of footprints or tracks; therefore, classification was performed based on differences in walking features. The classification procedure is illustrated in Figure 4. First, the footprint images were classified into those alternated on the left and right sides, and those in which both footprints of hind legs were left side by side (Group D) based on differences in walking style. Next, focusing on differences in ground conditions, the group of footprints images on alternating left and right sides was classified as having been left in soil or snow (Group C). The images left in soil were further classified into those in which two footprints were left on each side (Group A2) and those in which footprints were left in a straight line (Group B2) based on the differences in walking features. The results of the group classification for the nine animal species are summarized in Table 2.

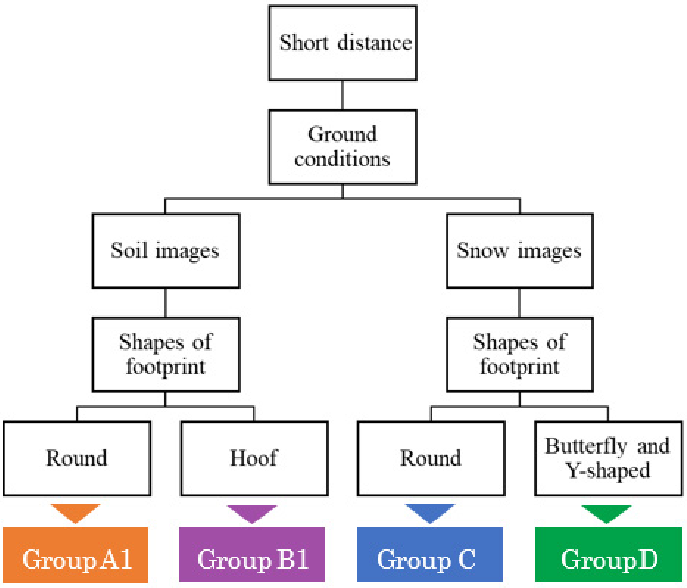


Figure 3. Classification procedure for image of footprints recorded at short distance

Table 1. Result of grouping footprints recorded at short distance

	Species
Group A1	Procyon lotor, Mustela itachi, Nyctereutes procynoides albus, Ursus arctos yesoensis, Vulpes vulpes schrencki
Group B1	Cervus nippon yesoensis
Group C	Nyctereutes procynoides albus, Martes melampus
Group D	Sciurus vulgaris orientis, Lepus timidus ainu

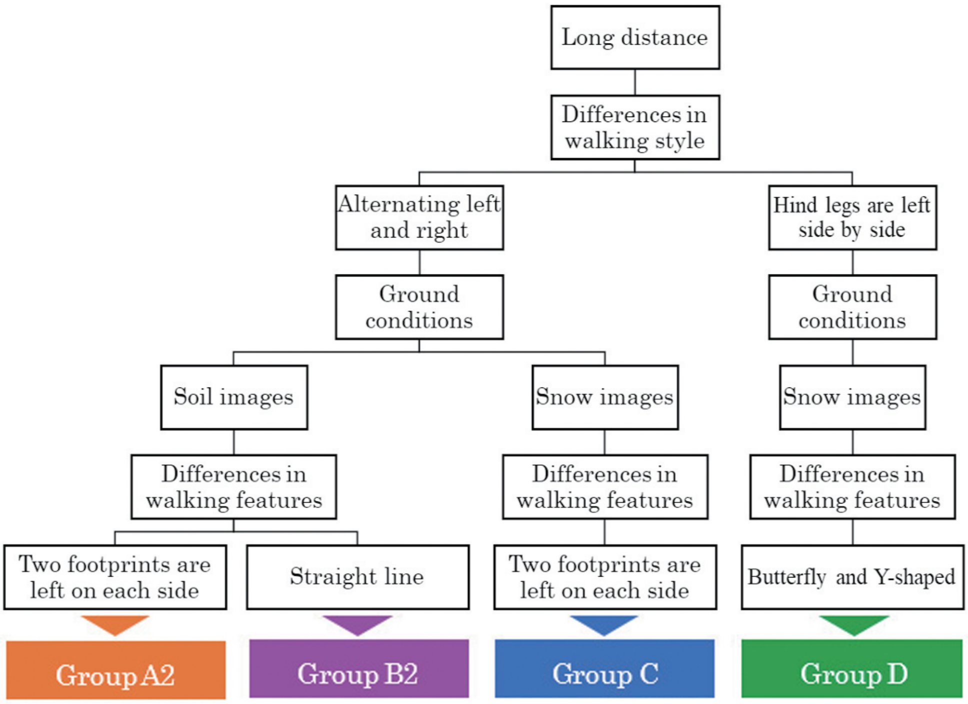


Figure 4. Classification procedure for images recorded at long distance

Table 2. Results of grouping images recorded at long distance

	Species
Group A2	Procyon lotor, Mustela itachi, Nyctereutes procynoides albus, Ursus arctos yesoensis
Group B2	Cervus nippon yesoensis, Vulpes vulpes schrencki
Group C	Nyctereutes procynoides albus, Martes melampus
Group D	Sciurus vulgaris orientis, Lepus timidus ainu

3.2. **Preprocessing.** To extract useful features for species discrimination, we performed preprocessing to extract the footprint areas from the images.

3.2.1. *Resizing.* A resizing process was conducted to unify the data conditions. The separate processes to be conducted were determined based on the footprint areas of each group. First, with the direction of travel against the footprint area, groups A1, A2, B2, and C were trimmed to fit the footprint area into a square, and group D was trimmed to fit the footprint area into a rectangle with an aspect ratio of 3 : 2. Next, the images were resized to 200×200 pixels for groups A1, A2, B2, and C and to 300×200 pixels for group D.

3.2.2. *Binarization.* To distinguish between footprint and non-footprint areas, the images were converted to grayscale and then binarized using an adaptive threshold [9,10]. We used adaptive thresholding to suppress the noise that occurs when the difference in pixel values between footprint and non-footprint areas is small, as thresholding addresses differences in pixel values in different images.

3.2.3. *Noise removal processing.* To clarify the area of the footprints, noise was removed in group B2 only. The noise-removal process was separated into three steps to leave the footprints for each group intact. Median filtering, dilation, and contraction processing were applied to the footprint images. Figure 5 shows the results obtained after applying preprocessing. In addition, a labeling process was applied to the footprint images for all groups other than group B2, and subsequently, an area removal process was performed through thresholding. Figure 6 shows the results obtained for the preprocessed footprint groups A1 and A2.

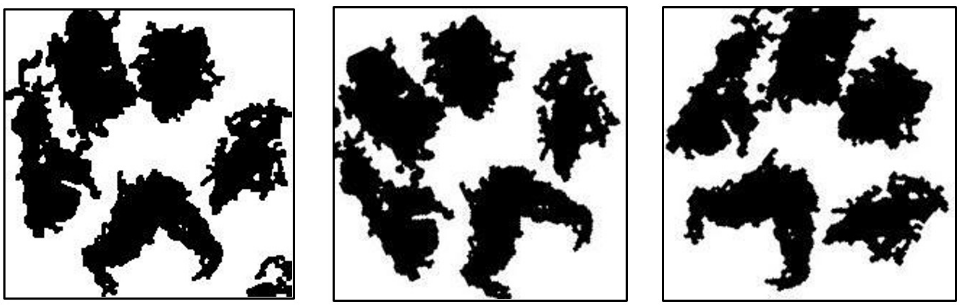
Normalized image (200×200 pixels) Binary image Noise reduction

Figure 5. Preprocessing for footprints of group B2

3.3. **Discrimination.** In this study, a CNN [11] was used to estimate species from the footprint images. First, data augmentation was performed on the preprocessed images to create the dataset used to train the model. Examples of the images from the dataset are shown in Figure 7. The dataset was fed into the CNN training model. The model combined convolutional, pooling, flattened, dropout, and fully connected layers. To avoid

Normalized image (200 × 200 pixels) Binary image Noise reduction

Figure 6. Preprocessing for footprints of groups A1 and A2



Preprocessed image Data augmented images

Figure 7. Example images of the dataset

overtraining, each node in the dropout layer was invalidated with a probability of 30.0%. Finally, the trained model was used to estimate the species shown in the preprocessed images.

4. Experimental Results and Discussion.

4.1. Species estimation. The species estimation results for each group are summarized in Table 3; an average accuracy of 94.5% was obtained. The accuracy of the results without grouping was 57.4%. The results suggest that grouping allowed the model to learn features between types with similar characteristics, leading to highly accurate estimation. Therefore, it may be possible to efficiently discriminate larger numbers of species by grouping them according to the environments in which the images were captured and the features of the footprints themselves.

4.2. Evaluation of the proposed species discrimination method. A cross-validation was conducted to evaluate the usefulness of the proposed method. First, the dataset

Table 3. Results of species estimation for each group

	Accuracy [%]
Group A1 (5 species)	89.6
Group A2 (4 species)	88.7
Group B2 (2 species)	100.0
Group C (2 species)	100.0
Group D (2 species)	94.4

Table 4. Results of cross-validation for each group

	Accuracy [%]
Group A1 (5 species)	89.9
Group A2 (4 species)	87.4
Group B2 (2 species)	90.2
Group C (2 species)	95.9
Group D (2 species)	92.8

for each group was divided into five equal parts. Four datasets were used to perform training, and the remaining datasets constituted the testing set. The results are summarized in Table 4. Overall, they show that the proposed approach proved useful in discriminating nine types of animals. Along these lines, a method proposed in prior work inputs the lengths of the digits in footprints to a support-vector machine (SVM) model as a feature [8]. However, because we targeted the footprints of nine species of animals, in this work, we considered that good accuracy could not be obtained using only the digit length feature. In contrast, the proposed method performs opportunity learning to learn a variety of features, and thus can handle many species of animals.

5. **Conclusion.** In this study, we have proposed a method to distinguish different species of animals using a CNN model, whereby nine species were successfully discriminated. The proposed grouping method was able to effectively and efficiently distinguish the species of the animals that left the footprints in the images used, successfully classifying nine species with an average accuracy of 94.5%. In future research, we intend to develop an appropriate preprocessing method for different ground conditions to improve the versatility of the discrimination method and automate the grouping process.

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