Method for Identification of Individual Flamingos Based on Movement Logs

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Abstract: This research aims to enable non-wearing and non-contact identification of individual animals. As an approach to this goal, we examined the feasibility of an identification method using movement logs, which is one of the animal behaviors. In this study, flamingos kept in a zoo were targeted. In order to collect the movement logs of flamingos, we developed a system in YOLO to identify individual flamingos and record their locations based on videos taken in the zoo's keeping area. In addition, we analyzed the collected movement logs of multiple individuals using a neural network and found that the movement logs could be used to detect individuals with higher identification accuracy than random inference for individual identification. Furthermore, we showed that the location where individuals tend to stay and the posture they tend to adopt change depending on conditions such as weather (rainy or cloudy) and the time of day (noon time period). This research indicates the feasibility of identifying individuals by their movements.

1 INTRODUCTION

Researchers examine the age and lifespan of individual animals in the field of wildlife herpetology and animal behavior. Animal keepers manage the health and care of their animals or identify them when they go missing. Animal identification is important in the biological study and management of these animals. Identification methods that involve contact with the animal or attachment of an instrument are in widespread use around the world (Silvy, 2012) (Ahmad, 2022).

The World Organisation for Animal Health (WOAH) has established five basic principles in animal welfare, defined as "the physical and mental state of an animal in relation to the conditions in which it lives and dies" (WOAH, 2023).

i. freedom from hunger, thirst, and malnutrition
ii. freedom from fear and distress
iii. freedom from physical and thermal discomfort
iv. freedom from pain, injury, and disease
v. freedom to express normal patterns of behavior

Contacting the animal or wearing an instrument for identification may cause ii through v of these to not be satisfied. Some previous studies (Silvy, 2012) (Ahmad, 2022), indicate that contact with animals or wearing equipment causes “fear”, “distress”, “physical discomfort”, “pain” or “injury”. In addition, these factors can cause “disease” and failure to express “normal patterns of behabiour”. Therefore, it is necessary to adopt a method that does not interfere with the animal's body in order to identify individuals while satisfying the five basic principles.

The goal of this research is to enable non-contact and non-wearing identification in accordance with the basic principles of animal welfare. As an approach, we focus on behavioral features whose effectiveness has not yet been verified. Among various types of behavior, behavior that all animals engage in is migration. Therefore, this study examines the feasibility of individual identification using animal movement logs. This paper describes the development of a system for acquiring movement logs, and then reports the results of the verification on the feasibility of individual identification using movement logs.

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2 EXISTING RESEARCH ON ANIMAL IDENTIFICATION WITH PHYSICAL INTERFERENCE

Individual identification methods involving physical interference can be broadly classified into three types: marking, tagging, and embedding. Marking is a method of placing visual landmarks on the animal's body. Examples include freeze branding, tattoos and notching on ears (Silvy, 2012) (Ahmad, 2022). Tagging is a method of attaching an artifact to the animal's body that serves as a symbol. Examples include ear-tags and bands (Silvy, 2012). Embedding is a method of implanting a microchip or other device into the body in which bioinformation to be managed is written.

Walker et al (Walker, 2011) evaluated heart rate, respiratory rate, and behavior of Steller's sea lions under general anesthesia when branded with a hot iron for identification. The results showed that heart rate and respiratory rate increased and body movements and tremors increased during branding. The authors concluded that anesthetized Steller's sea lions may feel pain during branding.

Lay et al (Lay, 1992) evaluated blood composition, heart rate, vocal rate, and the difference between the body temperature at the branding site and that at the same site opposite the branding site when calves were subjected to hot-iron branding, freeze branding, or sham branding at the same temperature as room temperature for individual identification. Results showed that plasma epinephrine, a blood component that increases with psychological stress, was increased in hot-iron branded calves. Heart rate was greater in calves that were hot-iron branded or freeze branded, and calves that were hot-iron branded or freeze branded vocalized. Differences in regional body temperatures were reported to be greater between freeze-branded and hot-iron calves.

Burley et al (Burley, 1982) studied the effects of the color of plastic tags attached to zebra finches on reproductive behavior. The authors summarized that female zebra finches prefer males with red plastic color bands and tend to avoid light blue and light green male ones, while male zebra finches prefer black and pink females and avoid blue and light green female ones.

Carminato et al. (Carminato, 2011) reported the presence of a microchip in a tumor surgically removed from the body of a cat and concluded that the microchip caused a foreign body reaction, although very rare, resulting in fibrosarcoma. Thus, it can be confirmed that implantation can cause disease.

Therefore, it is necessary to use identification methods that avoid physical interference, since individual animal identification involving it may not achieve the basic principles of animal welfare.

3 IDENTIFICATION METHOD USING BEHAVIORAL FEATURES

3.1 Comparison of Physical and Behavioral Features in Identification

In recent years, AI has begun to be actively used in non-contact and non-attached identification methods. There are two main types of AI-based identification methods: physical feature-based methods and behavioral feature-based ones.

Methods based on physical features utilize data on visual features of the animal's body. These include the identification of sea turtles by the scale patterns on the sides of their heads by Karun et all (Karun, 2021) and the identification of chimpanzees using their faces by Schofield et all. (Schofield, 2019). Basically, still images or videos are used as training data. In the case of still images, the input data is used as-is or with necessary portions cropped. The AI is trained based on these data to create a classifier for individual identification. In the case of video, after clipping a still image for each frame from the video, the same procedure is used to create a discriminative AI. Methods based on physical features are limited because they allow AI to use as training data only a portion of the moment when individual identification becomes possible.

In methods based on physical features, individual identification is based on appearance information, which is subject to change depending on physical growth and environmental conditions. When the appearance of an individual changes, there is a high possibility that the data that was previously acquired and used for training will no longer be usable. On the other hand, in the method based on behavioral features, individual identification is performed based on information that reveals the habits, personality, and customs of the individual. Since these are less likely to change compared to appearance, the acquired information can be used for a long period of time. In addition, there are few studies on individual identification methods using behavioral features other than those in the literature (Suzuki, 2021), and there are no studies that summarize their effectiveness. Therefore, in this study, we use behavioral features to identify individuals.

3.2 Behavior Used for Individual Identification

To explore behaviors that could be used for individual identification, we first observed behaviors of familiar animals. As a result, we noticed that some breeding cats prefer to stay in certain places, and that turtles in ponds come up to the land to sunbathe at certain times of the day. Since these phenomena are caused by movement among behaviors, there is a possibility that individual animals can be identified based on movement data. Therefore, in this study, we focus on "movement logs" among behaviors to identify individual animals.

3.3 Selection of Animals to Be Identified

With the cooperation of Yagiyama Zoological Park, we selected animals for identification in this study. The criteria for selection were that there must be multiple individuals of the same species, including related species; that two or more individuals must be kept or exhibited in the same space; that all target animals must move frequently within the space; and that the animals must not be interested in touching or destroying the set-up equipment. After selecting animals that met these conditions, we decided to conduct this study on flamingos.

The flamingos kept at the zoo are European greater flamingo (Phoenicopterus ruber roseus), Chilean flamingo (Phoenicopterus chilensis), Caribbean flamingo (Phoenicopterus ruber), totaling 17. All but the Caribbean flamingo have a color tag on their right or left leg to uniquely identify them within the species. Some European flamingos and Chilean flamingos have overlapping colors on the left and right sides of their legs and color tags.

We selected four flamingos for this study. Their species and tag correspondence are shown in Table 1. Based on the color of the tag and the left and right sides of the legs, we named them "Rblue", "Lblue", "None" and "Rblack".

Table 1: Correspondence between flamingo species kept at the zoological garden and color tags.

Species	Left Leg	Right Leg
European greater flamingo	blue	none
European greater flamingo	none	blue
Caribbean flamingo	none	none
European greater flamingo	none	black

4 DEVELOPMENT OF THE SYSTEM TO OBTAIN FLAMINGO LOCATION INFORMATION

4.1 Overview of the System

To achieve the objective of this study, we developed a system to verify the feasibility of flamingo identification using movement logs. First, we captured video of flamingos to obtain movement data. Next, we created a flamingo detection model using YOLO. Finally, we recorded location information from the movement data of each individual flamingo detected by the model.

4.2 Collection of Video Data

To obtain flamingo movement logs, We captured video images from inside the breeding space (Figure 1). We selected the shooting location because it was easy for flamingos to gather and because it was possible to shoot from a horizontal angle. We used Samsung Galaxy A7 as our photographic equipment. The shooting period was from July 4 to October 22, 2023, from 9:00 a.m. to 5:00 p.m. To prevent thermal runaway of the equipment, we took video in a cycle of 30 minutes of shooting followed by 10 minutes of standby.

Figure 1: Angle of view 4 from inside the breeding space.

4.3 Creation of a Custom Learning Model for Individual Flamingo Detection Using YOLO

As a preliminary step to identify individuals using movement logs, it is necessary to record which individuals are in which locations in the video. Therefore, we created a flamingo individual detection model using YOLO v8 to automatically record the X and Y coordinates representing the position. To generate training data to identify each individual, we manually linked the position of the flamingo in the video to the individual. We identified and linked individuals using color tags attached to the left and right legs. However, some individuals had overlapping left and right color tags, making manual identification difficult, so we annotated only those individuals for which the left and right leg color and color tag color were completely unique for all species. Four of the individuals were frequently seen in the angle of view of the camera, so we created a training model for them.

To prepare the annotation, we cut one frame per second from a 30-minute movie (pixel count: 1920px×1080px, frame rate: 30fps) and saved each frame as a jpg file. To avoid running out of memory during training, we downscaled the number of pixels to 960px×540px. For annotation, we used labelImg and labeled each flamingo as a class. The train data was annotated based on a total of 4282 images from the videos of October 11-22, 2023, and the validation data was annotated based on a total of 3167 images from the data of September 4-13, 2023. Training was performed for 100 epochs based on the yolo8n.pt model, and a custom training model was created. Figure 2 shows the training results. The six items from the middle to the left are losses, which indicate the error between the percentage of correct answers and the predicted value. If they move to the lower right, we have achieved good learning. The four items to the right of the middle are “precision”, “recall”, “mAP50” and “mAP50-95”. If they move to the upper right, the learning is good. Learning was generally good except for “precision,” which indicates the percentage of true positives out of all positives. What we did to compensate for the low “precision” is described below in section 4.5.

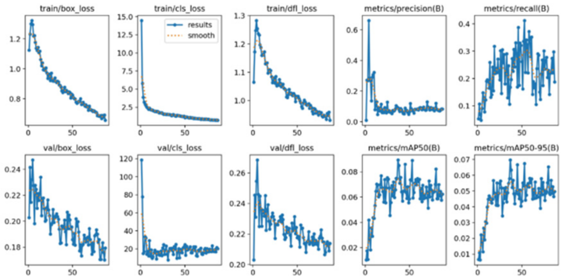

Figure 2: Result of the custom learning model. ‘loss’ and ‘precision’ moved to the lower right. ‘recall’, ‘mAP50’ and ‘mAP50-95’ moved to the upper right.

4.4 Extraction of Location Information

We used videos taken between September 20 - 27, 2023 as the original data from which we extracted location information. To avoid memory shortages during inference, we downscaled the pixel size from 1920px×1080px to 960px×540px. We performed inference on the data using the custom training model we created, and saved the results in a CSV file and in a video file with the Bounding Box added. In the contents of the CSV file shown in Table 2, “x1”, “y1”, “x2” and “y2” are the coordinates of the Bounding Box detected by inference (x1 is the X coordinate of the left side, y1 is the Y coordinate of the upper side, x2 is the X coordinate of the right side, and y2 is the Y coordinate of the lower side). “class” is the class name of the detected object (0 for Rblue, 1 for Lblue, 2 for None, 3 for Rblack). “confidence” is the probability that the detected object's ”class” is correct. In this study, this coordinate data is treated as a location data set.

4.5 Modification of the Location Data Set

Figure 2 shows that the “precision” value remained at a low value around 0.1 even after further training. The current position data set contains a large amount of erroneous data. Therefore, it may be difficult to distinguish true positives from false positives. To verify the feasibility of individual identification more

Table 2: Example of the contents of a saved CSV file.

x1	y1	x2	y2	class	confidence
387.57	176.61	426.84	362.69	none	0.51
82.58	130.03	182.07	419.71	Lblue	0.51
218.10	275.05	271.28	388.94	Rblue	0.58
204.60	290.04	270.67	391.59	Rblack	0.65

accurately in the subsequent validation, we modify the data. It reduces the number of erroneous data in the location data set.

Comparing the location data set and the saved video obtained in the previous section, we modify the data by manually deleting the false positives. The data to be deleted are those with incorrect class and those whose errors can be easily identified by the color of the color tag or by the lack of positional coverage. We did not perform the procedure to re-label the data correctly. The number of records after data examination was 427,252.

5 FEASIBILITY OF LOCATION-BASED FLAMINGO IDENTIFICATION

5.1 Hypothesis on the Location of Individual Flamingos

In this study, we hypothesized that each individual flamingo tends to stay in a certain location. By testing this hypothesis, we examine the feasibility of flamingo identification based on location information.

5.2 Method for Testing Hypotheses

Based on the location data set extracted in Chapter 4, we will verify whether or not a particular individual tends to stay within the location shown in the video. We use neural network (NN) as a verification method. We added "weather" and "time" to the location data set to account for possible changes in individual behavior due to weather and time period effects (Table 3). "weather" is weather information observed and published by Japan Meteorological Agency. During the period under verification, "clear", "sunny", "slightly cloudy", "cloudy" and "rainy" were observed. Since the weather information was announced every three hours from 0:00, we entered the same weather conditions for the three hours after the observation time. "time" is the time when the image was taken. We verify by changing these under which the number of records vary.

From the items in Table 2, we select the objective variable as "class" and the explanatory variables from the other items. Among the explanatory variables, "x1" and "x2" represent the horizontal position. We removed "x2" because the correlation coefficient was 0.99, which is an extremely strong positive correlation and multicollinearity was observed. y1" and 'y2' represent the depth position or orientation. Since their correlation coefficient was 0.26, we judged that there was no multicollinearity and decided to use both as explanatory variables. Since "confidence" is an item unrelated to location information, we removed it from the explanatory variables.

The number of codes in the location data set used for verification is 631,486. The objective variable "class" is an integer from 0 to 3. The explanatory variable "x1" is a number between 0 and 960. "y1" is a number between 0 and 960. "y2" is a number greater than 0 and less than or equal to 960.

We judge the results by the value of accuracy, which represents the correctness rate of the discriminator when using all the data in the location data set, both training and validation data, and the value of val_accuracy when using only the validation data in the location data set. The number of training epochs is 100.

5.3 Results of Hypothesis Testing

5.3.1 Results for All Data

The accuracy at the 100th epoch was approximately 0.53, and the val_accuracy was approximately 0.56. To confirm that there is a significant difference between the small value of 0.53 and the random inference value of 0.25, we tested the null hypothesis that "there is no significant difference between the percentage of correct answers (0.53) and the random inference value (0.25)" and tested the difference in mother proportions. As a result, we were able to show the correctness of the hypothesis because the p-value was 0.000049220, a significant difference at a significance level of less than 1%.

Table 3: Example of location data set plus information on shooting time and weather.

x1	y1	x2	y2	class	confidence	weather	time
387.57	176.61	426.84	362.69	2	0.51	clear	1350
82.58	130.03	182.07	419.71	1	0.51	sunny	950
218.10	275.05	271.28	388.94	0	0.58	cloudy	1630
204.60	290.04	270.67	391.59	3	0.65	rainy	1150

5.3.2 Results with Data by Weather

We verified six patterns of weather. The results are shown in Table 4. The results show that the highest accuracy is approximately 0.60 for validation number 6, which indicates rainy weather, and the highest val_accuracy is approximately 0.64 for validation number 3, which indicates cloudy weather. In the same way as for the NN test using all the data, we confirmed that there was a significant difference between the accuracy (0.54) for validation number 2, which had the lowest value, and the random inference value (0.25), by testing the difference in the mother proportions. As a result of testing the null hypothesis that "there is no significant difference between the percentage of correct answers (0.54) and the random inference value (0.25)," the p-value was 0.00002731, showing that there was a significant difference at a significance level of less than 1%.

5.3.3 Results with Data by Time Period

We verified three patterns of time period. The results are shown in Table 5. The results show that the highest accuracy is approximately 0.59 for validation number 1, which indicates the time period from morning to noon, and the highest val_accuracy is approximately 0.63 for validation number 2, which indicates the time period during the daytime. In the same way as for the validation using all the data, a test of difference in proportions was conducted to confirm that there was a significant difference between the accuracy (0.58) for validation numbers 2 and 3, which were the lowest values among the results obtained, and the random inference value (0.25). As a result of testing the null hypothesis that "there is no significant difference between the percentage of correct answers (0.58) and the random inference value (0.25)," the p-value was 0.000002182, showing that there was a significant difference at a significance level of less than 1%.

5.4 Analysis of Verification Results

Based on the results obtained in the previous section, we inferred that under certain conditions, the location at which individuals tend to remain and the position at which they tend to take up positions may change. Therefore, in this section, we analyze the tendency of the position where individuals tend to stay, the posture they tend to take, and the individuals that can be identified under each condition. In the weather verification, the percentage of correct answers was higher in rainy or cloudy weather. In the time of day verification, the percentage of correct answers was higher during noon time period. Therefore, we analyze the results for these conditions.

We describe the analysis method. First, we divide the X-coordinate into 10 segments of 96px each. Next, we measure the number of x1 in the location data set that fall within the segmented area. We analyze by finding the first most frequent region (mode) and the second most frequent region (second mode) for each individual under each condition, and comparing them with the mode and second mode of all the data. After dividing the Y-coordinate by 54px, we find the mode and the second mode by the same procedure as for the x-coordinate. Table 6 lists the number of x1 for each condition of Rblue as an example of data to support the analysis.

Table 4: Verification results considering weather conditions.

Verification number	Record count	Weather	accuracy	val_accuracy
1	43,638	clear, sunny	Approx. 0.58	Approx. 0.62
2	103,128	clear, sunny, slightly cloudy	Approx. 0.54	Approx. 0.62
3	213,952	slightly cloudy, cloudy	Approx. 0.59	Approx. 0.64
4	383,615	slightly cloudy, cloudy, rainy	Approx. 0.55	Approx. 0.57
5	324,125	cloudy, rainy	Approx. 0.58	Approx. 0.60
6	169,663	rainy	Approx. 0.60	Approx. 0.62

Table 5: Verification results considering time period.

Verification number	Record count	Time period	accuracy	val_accuracy
1	211,339	9:10 - 12:20	Approx. 0.59	Approx. 0.61
2	141,068	11:10 - 13:00	Approx. 0.58	Approx. 0.63
3	215,912	12:20 - 17:00	Approx. 0.58	Approx. 0.61

Table 6: Number of x1 in each condition for Rblue.

X-coordinate	all	cloudy	rainy	noon time period
0≦x1≦96	1,415	812	551	0
96＜x1≦192	4,540	703	2,895	1,233
192＜x1≦288	11,957	6,330	5,187	3,851
288＜x1≦384	11,701	4,955	6,717	5,262
384＜x1≦480	23,513	12,069	8,682	8,982
480＜x1≦576	6,648	939	3,084	3,447
576＜x1≦672	12,741	6,760	5,841	2,068
672＜x1≦768	12,010	2,958	7,465	3,859

5.4.1 Analisis of All Data

Figure 3 shows the distribution of the positions and postures at which each flamingo tends to stay in all the data.

Comparing the images of the distribution for all the data with each condition, we describe the changes in the position and posture that tend to stay under each condition. If x1 which is the left edge of the body changes, it indicates a change in the horizontal position. If y1 which is the upper edge of the head or body changes, it indicates a change in the posture that is easy to take. If y2 which is the toe of the foot changes, it indicates a change in the vertical position.

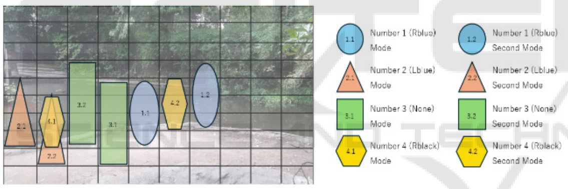

Figure 3: The location and posture of each flamingo in all the data.

5.4.2 Analysis of Cloudy Weather

The left panel of Figure 4 is the distribution of the most likely positions and postures of individuals for all data. The right panel of Figure 4 shows them in cloudy weather. 4 individuals are almost completely uncovered, so all individuals can be identified when it is cloudy.

"Rblue" changes easier posture to take. "Lblue" changes easier posture to take. "none" changes horizontal and vertical position. "Rblack" changes easier posture to take.

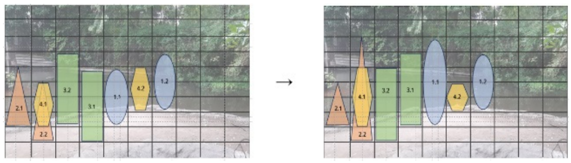

Figure 4: Comparison of distribution between all data and cloudy weather. Blue circles are Rblue, red triangles are Lblue, green squares are None, yellow hexagons are Rblack, 1 decimal place is the mode and 2 is the second mode.

5.4.3 Analysis of Rainy Weather

The left panel of Figure 5 is the distribution of the most likely positions and postures of individuals for all data. The right panel of Figure 5 shows them in rainy weather. Because the distribution of individuals covers some areas, only some individuals (Rblue and Rblack) can be identified when it is rainy.

"Rblue" changes horizontal and vertical positions and easier posture to take. "Lblue" changes horizontal and vertical positions and easier posture to take. "none" changes the horizontal and vertical positions. "Rblack" changes horizontal position and easier posture to take.

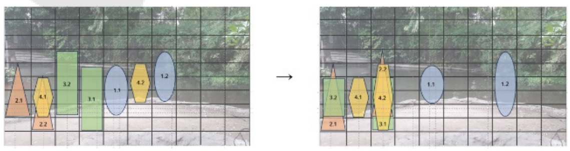

Figure 5: Comparison of distribution between all data and rainy weather. Blue circles are Rblue, red triangles are Lblue, green squares are None, yellow hexagons are Rblack, 1 decimal place is the mode and 2 is the second mode.

5.4.4 Analysis in the Noon Time Period

The left panel of Figure 6 is the distribution of the most likely positions and postures of individuals for all data. The right panel of Figure 6 shows them during noon time period. Because the distribution of individuals covers some areas, only some individuals (Rblue, Lblue and none) can be identified when using the data from rainy conditions.

"Rblue" changes horizontal position. "Lblue" changes horizontal position and easier posture to take. "none" changes horizontal position. "Rblack" changes horizontal and vertical positions and easier posture to take.

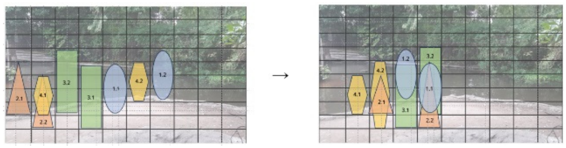

Figure 6: Comparison of distribution between all data and noon time period. Blue circles are Rblue, red triangles are Lblue, green squares are None, yellow hexagons are Rblack, 1 decimal place is the mode and 2 is the second mode.

6 SUMMARY AND FUTURE ISSUES

To show the feasibility of individual identification based on behavioral features of animals, we verified that individual identification is possible with movement logs of flamingos. By creating a system to collect location data set and testing hypotheses using a neural network, we demonstrated the feasibility of individual identification based on flamingo location data. In addition, we were able to show that the location where each individual tends to stay and the posture it tends to take change according to each condition. On the other hand, there is room for improvement in this study because some data were detected incorrectly when the location data set was created by individual detection in YOLO, which may have affected the accuracy of the data and affected subsequent validation.

In this study, we identified individual flamingos using two-dimensional images extracted from videos. Although it is difficult to obtain three-dimensional data in a complex natural environment, the method in this study may be able to obtain data and identify individuals in such a situation.

There is room for improvement in this study because the existence of false positive data when creating the position data set by individual detection in YOLO may have affected the accuracy of the data, which may have affected subsequent validation. In addition, the number of individuals and flamingo species studied were 4 and 2, respectively, limiting the generalizability of the findings.

As future tasks, it is necessary to verify the accuracy of the location data set, to show that other individuals can be identified using the method in this study, to show what postures they take under different conditions, to show that it is possible to identify individuals by movement for other animals, and to show that it is possible to identify individual animals by other behaviors. We will also increase the number of individuals and flamingo species studied for a more extensive and longitudinal validation.

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