Real-time on-board artificial neural network based processing of sensory data in birds

The study of movement ecology benefited from the development of advanced biologging techniques (Borger et al. 2020; Williams et al. 2019). Here, biologging refers to “the use of miniaturized animal-attached tags for logging and/or relaying of data about an animal’s movements, behaviour, physiology and/or environment” (Rutz & Hays, 2009). Increasingly, the tracking of animals is combined with tri-axial accelerometer (**ACC**) data. An ACC is an electromechanical device used to measure acceleration forces and used to study (animal) behaviours across a wide range of species alongside positional information. Tri-axial ACCs, which sense accelerations of three orthogonal axes (i.e., anterior-posterior:surge, medial-lateral:sway, inferior-superior:heave, Nathan et al., 2012) have typically been used in various ecological studies. Activity levels of animals represented by summaries of ACC data have been used for a wide and diverse array of applications. Although an ACC has versatile applications in ecological studies, it also has limitations. For bird tracking, the total weight of the tag and accessories (i.e., the tag itself and the items, such as a harness necessary to mount the device to the animal) should be less than 5% of the bird’s body mass to minimize the impact that the logging device has on the bird’s behaviour (Portugal & White 2018). Therefore, the on-board battery size and thus capacity is limited by the weight constraints to the tracking device. One approach to extend the research time span using ACC devices is to sample the data intermittently, but a clear drawback of this intermittent sampling procedure is the loss of potentially valuable data. Another approach to extend the research time span using ACC devices may the use of edge computing. Edge computing is the deployment of computing resources close to the data source. Recently, on-board data processing through edge computing was successfully used to simultaneously reduce accelerometer data volume and transmission power consumption, allowing long-term, continuous behavioral monitoring of Pacific black ducks *Anas superciliosa* (Hui et al., 2022). The disadvantage of their approach, however, is that feature calculations will be different across different animal species, hindering the data processing pipeline for automation. Deep learning models could extract features from raw data through model structure and therefore can serve as a solution for a generic use.

This research aims to develop a pipeline to automatically extract behaviours from raw ACC data on-board of animal tracking devices. We used pied flycatcher as the research species. The pipeline includes three steps: First, animal tagging and raw ACC data collection; Second, deep learning model development (for edge computing), and third the deployment of new loggers with the developed edge computing model. Each of these steps is briefly discussed below.

Animal tagging and raw ACC data collection The accelerometer loggers used in this study were developed by the Electronics lab at the Department of Biology, Lund University, Sweden (see for more details [1]). The loggers were programmed to start logging tri-axial acceleration at the next full hour after the hour from activation. Once logging started, the logger recorded data continuously for about 30 min, limited by on-board memory size that could hold approximately 175,000 individual 3-axis recordings. Experiments were performed with seven (pre-breeding) male European pied flycatchers caught in the wild at Vombs fure, Lund, Sweden. Each bird was weighed and ringed after being caught, and then transported to individual-based aviaries (measuring 5×3×2mtr in LxWxH) at the Stensoffa field station (55°41’42’’N, 13°26’50’’E), approximately 8 km west of the catching site. During captivity, birds were given food (i.e., mealworms) and water ad libitum. The captive periods ranged from 3 to 7 days, with the majority being kept for 3–4 days. All birds were released back to the capture site after the experiments. The mean total mass of the logger and bird was 12.72g. Each male European pied flycatcher went through one experimental session inside their housing aviary, during which we recorded their behaviours using both a body-attached accelerometer and a stereoscopic videography system (Figure 1). The accelerometer logger was attached to the animal over their synsacrum using a leg-loop harness. The videography system consisted of two high-speed cameras (GoPro Hero 4 [2]), positioned outside the aviary and oriented such that they filmed the middle of the aviary arena at oblique angles from two sides.

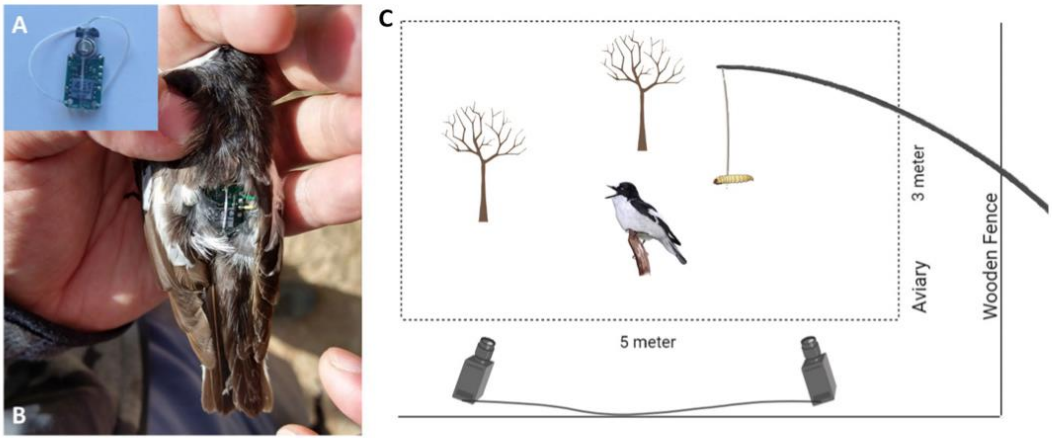

Figure 1. Aviary experimental setup. A. accelerometer logger. B. a pied flycatcher with logger by leg-loop harness. C. Aviary general view during an experiment.

At the start of the experiment, we manually started video recording and accelerometer logging. During the experiment, we triggered in-flight prey catching behaviour by providing the animal with a mealworm suspended from a fishing line in the middle of the region-of-interest filmed by the video system. If the bird would catch and eat the mealworm, we replaced it with a new one. Experiments and video recording continued for approximately 25 min. After each experimental session, the accelerometer logger was retrieved, and the data were downloaded. Accelerometer and video data were synchronized by first using the times indicated by the GoPro cameras and the loggers (started at activation), followed with a more accurate synchronization based on identified activities of the birds (e.g., flight initiation after a period of inactivity). We then used the video data to categorize seven different behaviours Table 1, including the high frequency behaviours of flying and food swallowing.

Table 1. Behaviour categories and their descriptions

Behaviour category	**Description**
Flying	Flying, including in flights intervals when the bird folded wings against the body
Preening	Preening feathers with beak
Food shaking	Shaking the head to stun food item in the beak
Perching	Sitting still on a perch
Swallowing	Swallowing prey by moving the head back and forth to assist the process
Bill wiping	Scratching the beak against the perch branch
Other	All behaviours other than the categories listed above

Deep learning model development (for edge computing) We used the Tensorflow library in Python for deep learning model training and validation. The deep learning model was used to predict the seven behaviours listed in Table 1 above. For model development we refer to the flow chart below (Figure 2).

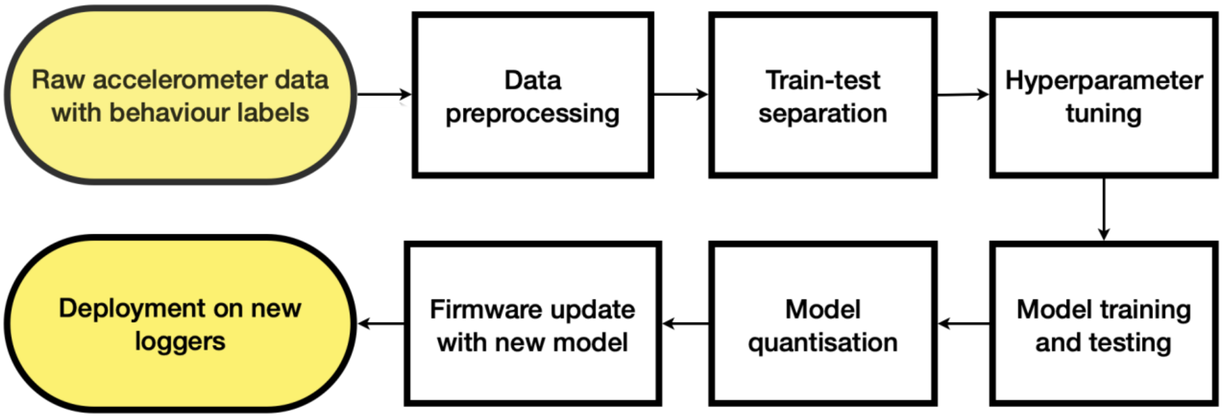

Figure 2. Flowchart for deep learning model development. The model is convolution neural network in this study.

Deployment of new loggers with edge computing model. In early 2023, a new logger was developed by our industrial partner Druid Technology [1]. We tagged 20 pied flycatchers in June 2023 with this new logger to collected raw ACC data similarly as described earlier in the section '*Animal tagging and raw ACC data collection'.* We tested the deep learning model on-board of five loggers. Therefore, we got raw accelerometer data as well as predicted behaviours from these five loggers.

Edge computing devices

Logger for raw accelerometer data

The loggers used in the 2022 experiment were small loggers (18×9×2mm, W×L×H) weighed 0.7 g and were powered by a zink-air button cell (A10, 100 mAh capacity). The accelerometer unit recorded three-axis accelerations (x-axis: lateral; y-axis: longitudinal; z-axis: vertical) with a sampling frequency at around 100 Hz, a measurement acceleration range of ±8 g (where g=9.81 ms−2), and an 8-bit output resolution for each axis. As a result, the loggers had 256 output levels at a resolution of 0.063 g. In 2023, a new logger was developed by our industrial partner Druid Technology (https://druid.tech/). The logger weighed 0.6g. It was equipped with an accelerometer for behaviour detection and a light sensor for light intensity sensing. The logger had on-board Bluetooth for data transmission. The on-board lithium battery (10 or 15 mAh capacity) allowed for recharging. The operation logics of the loggers was controlled by the on-board nrF52840 SoC (system on a chip), which also guaranteed the edge-computing capacity of the logger. The logger allowed for settings/operations customization. For example, we could change the sampling frequency of light intensity for bird nest-visit monitoring. Also, the sampling frequency can be set to match requirements for different animals (e.g., 100Hz for the studied pied flycatchers in the current research). Importantly, the logger allowed for edge computing models execution to process raw ACC data into behaviour codes (e.g, 1 for flying, 2 for resting etc).

Camera's

GoPro Hero 4 Camera

Two high-speed cameras (GoPro Hero 4) were positioned outside the aviary and oriented such that they filmed the middle of the aviary arena at oblique angles from two sides. The cameras recorded videos at a temporal resolution of 90 frames-per-second with a spatial resolution of 1920×1080 pixels. The two cameras were synchronized within a maximum 5 ns time lag, using custom-made sync electronics, which consisted of a 'Bastet' with 'MewPro 2' for the master camera, and a 'MewPro Cable' for the slave camera (Orangkucing Lab, Tokyo, Japan).

Real-time on-board neural processing in birds

There were two stages of data processing. In the 1st stage, raw accelerometer data with corresponding behaviour labels (Figure 3) were collected in aviary experiments. The loggers collected data at 100Hz. We used these data to train and validate deep learning model. The trained deep learning model was then quantized (i.e., reducing model storage and execution time by changing floating point parameters to integers). In the 2nd stage, the quantized deep learning model was uploaded to animal loggers for edge computing. When the updated loggers were used on new birds, they still recorded raw accelerometer data. But instead of storing all data, the edge computing model processed the data on-board of the loggers and only behaviour types were saved on the device memory (Figure 4).

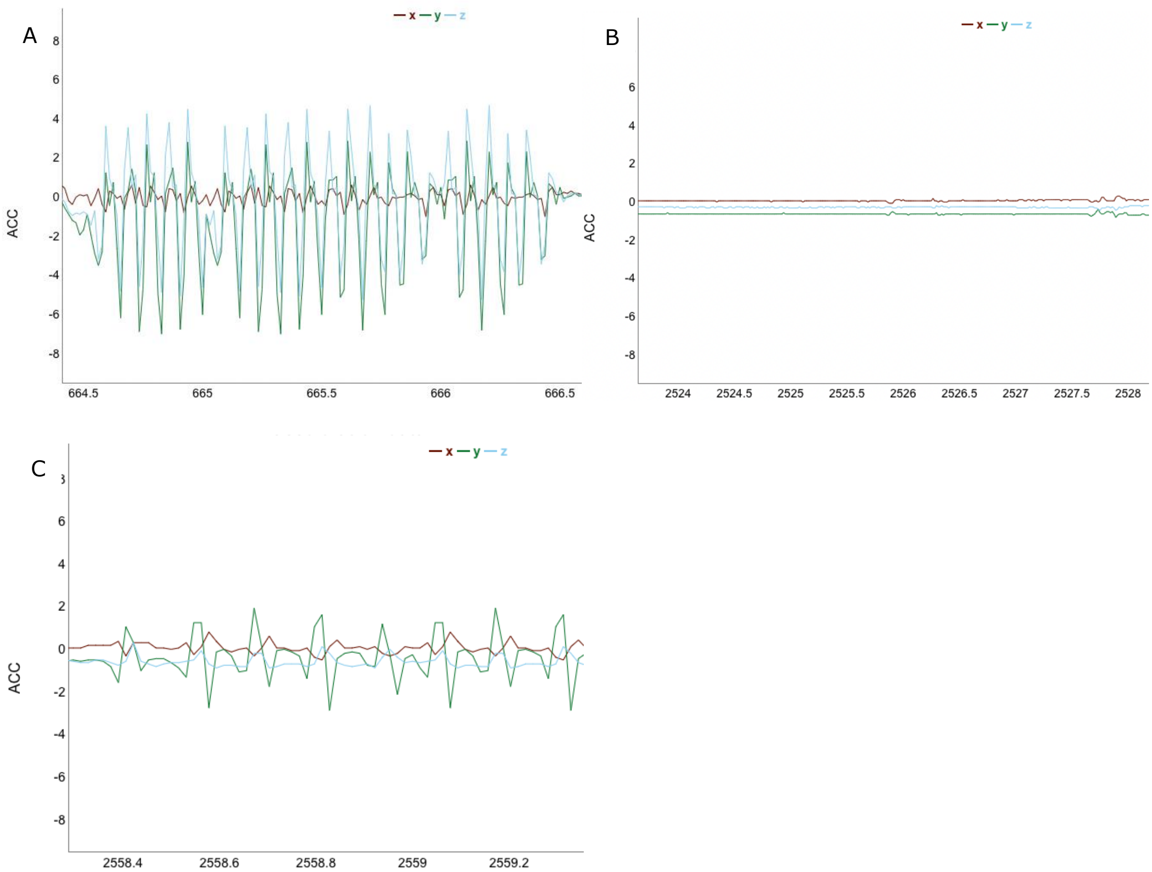

Figure 3. The raw accelerometer data collected by loggers on pied flycatchers. The x-axis indicates indexes of behaviour segments and 1 unit contains 0.64-second of raw ACC data, i.e., 64 groups of x (lateral movement), y (front and back movement), z (up and down movement) values. Unit of y-axis is g (1g = 9.8 m/s^2). A. Active flapping flights (fast wing flapping when flying). B. Perching (sitting still). C. Swallowing food (head and body move back and forth to swallow food item).

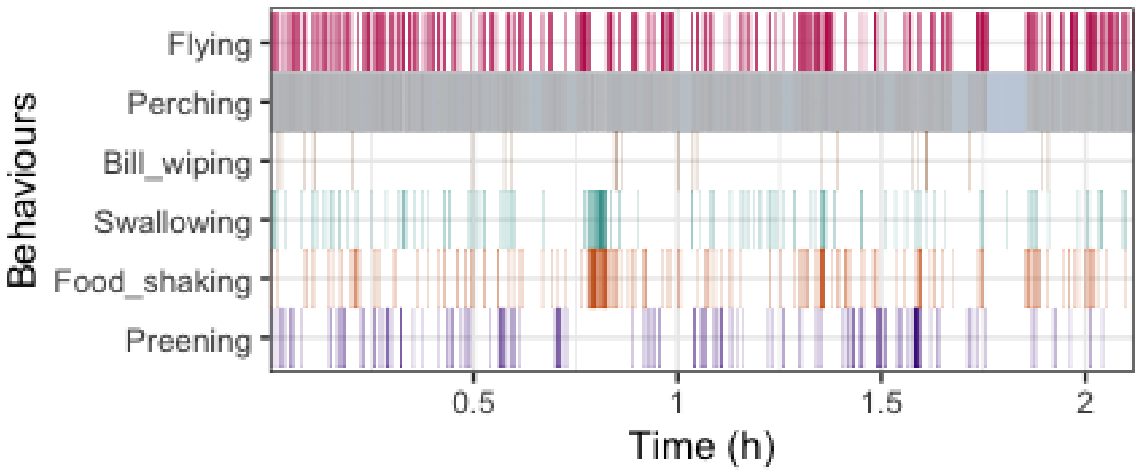

Figure 4. Behaviour time budget of a wild pied flycatcher (2 hours of recording). Each vertical bar represent a behaviour type of 0.64s duration.

Locations of scripts

Scripts are still under development (nearly finished) and will be organized later. Scripts will be stored in github.

Lessons learned

- Deep learning (here convolution neural network) is suitable for edge computing applications on small loggers. Although we only used accelerometer data for our application, the model framework will also be feasible if more data sources are used for behaviour classification, such as sensor data generated magnetometers and gyroscopes.
- The technology, i.e., edge computing with deep learning model applied on accelerometer data, can be used on other animal species, such as other avian species and mammals.

List of people involved and their role

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Output

Scientific output

Yu, H., F.T. Muijres, J.S. te Lindert, A. Hedenström. And P. Henningsson. 2023. Accelerometer sampling requirements for animal behaviour classification and estimation of energy expenditure. Animal Biotelemetry 11, 28. https://doi.org/10.1186/s40317-023-00339-w

Yu, H., G.J. Amador, A. Cribellier A., M. Klaassen, H.J. de Knegt, M. Naguib, R. Nijland, L. Nowas, H.H.T. Prins, L. Snijders, C. Tyson, F.T. Muijres. 2023. Edge computing in wildlife behaviour and ecology. Trends in Ecol Evo 39, 2. https://doi.org/10.1016/j.tree.2023.11.014

Presentations

Yu, H. 2022. 2022. Continuous on-board behaviour classification using accelerometry, a case study and ecological insights. Association for the Study of Animal Behaviour (ASAB) 2022 winter conference, Edinburgh, Scotland, United Kingdom, 6-7 December, 2022.

Yu, H. 2023. Accelerometer sampling requirements for animal behaviour classification and estimation of energy expenditure. International Wader Study Group 2023 conference, Sylt, Germany, 29 September – 3 October 2023.