

Visually supported annotation of bird tracking data and subsequent classification of behaviour using machine learning

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1. Introduction

Advances in animal tracking technology enable researchers to not only remotely collect large amounts of data on the whereabouts of tagged individuals, but to simultaneously provide information such as velocity, altitude, (ambient) temperature, pressure, depth, tri-axial acceleration, etcetera. Some of that extra collected data may be indicative of the actual behaviour of the animals carrying these devices, opening an enormous potential for e.g. ecological studies (Bouten et al. 2013). Thanks to these recent advances in hardware technology and storage capacity, data can be recorded at increasing rates and volumes, making studying bird behaviour a data intensive science (Demšar et al. 2015, Kays et al. 2015).

In order to monitor actual animal behaviour, information that was previously derived only from visual observations of the animals themselves, researchers need to convert and categorise the data collected with the tracking device. For example, soaring or actively flying (wing-flapping) birds produce a whole range of characteristic parameters (notably in speed and tri-axial acceleration) as raw data, but other behaviour may be more difficult to interpret.

Experts have learned from experience to visually recognize patterns in the accelerometer and other signals which correspond to a specific behaviour. Ideally all expert annotations are done using recorded video of the bird's behaviour, synchronised with the tracker device records (Bom et al. 2014). In practice, videos of birds with devices in their natural habitat are hard to obtain and often not feasible. An alternative to using video, is to manually annotate part of the data collected by the bird's device based on expert knowledge (Shamoun et al. 2012). Such expert annotation can be difficult and time consuming.

It is not feasible to manually interpret each record as specific bird behaviour for many thousands or millions of GPS and accelerometer records. Supervised machine learning (ML) can help to map raw data to behaviour classes of interest by applying trained models. Such a model can thus classify large amounts of data with low effort from a researcher. An expert needs to select and manually annotate a subset of the data to train a ML model.

To optimize an expert's annotation efforts, ideally, a toolbox would present all data relevant to the annotation process in a single user interface. Also, it would provide visualizations of the ML process, making training models an intuitive process. One toolbox, developed for this purpose is AcceleRater (Resheff et al. 2014). It is a web application that handles training ML models, visualizing results of the process, classifying data using the trained models, and spatially visualizing the classifications. This software does not, however, provide tools to manually annotate data or visualizations that could aid expert annotation.

In this paper we propose an integrated workflow for bird behaviour interpretation. The workflow includes expert annotation as well as ML, automated classification and review of the classifications as explained in Section 2. With our toolbox, we were able to significantly speed up the iterative process of improving the behavioural model. Section 3 describes a day of the life of a lesser black-backed gull that was interpreted using our system, and we draw conclusions in Section 4.

2. Research workflow

To address the challenges which ecologists face when studying bird movement and behaviour with tracking devices, we have developed integrated tools to facilitate and visually support the research workflow (Figure 1). We provide an Annotation Tool as a platform for the manual annotation process. The tool can also be used to visually interpret automatic classifications. Using a dataset, annotated with the Annotation Tool as input, researchers can train a ML model with our Classification Tool. The researcher can use the trained model to automatically assign classes to unannotated data. The iterative usage of both tools for annotation correction can improve the quality of the trainset, resulting in automatic classification with higher accuracy.

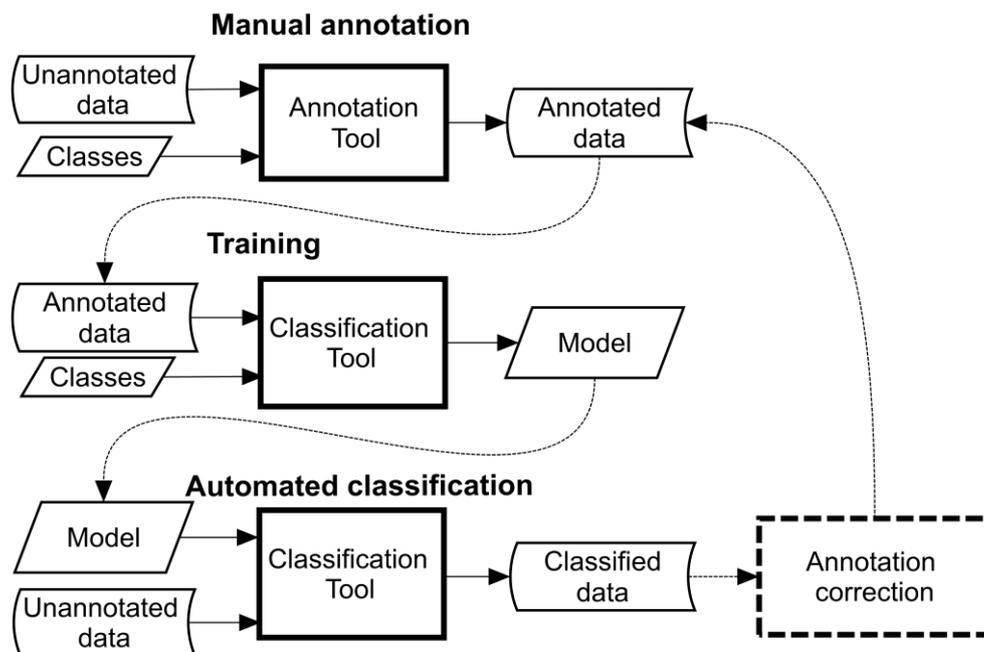


Figure 1. Annotation and classification of bird movement and activities workflow.

2.1 Annotation Tool

To manually annotate bird behaviour, the experienced researcher combines accelerometer data and contextual information such as videos of behaviour, the location of the bird on satellite imagery of the earth surface to annotate accelerometer data with "observed behaviour". To visualize all these data types, researchers generally use many separate software applications, e.g., Google Earth or GIS software for spatial data and environmental data and statistical software packages to create times series or summaries of data. To completely eliminate the labour intensive and error-prone process of data integration and synchronization of selected time and annotations across different software platforms, we have developed the Annotation Tool (Verhoeven 2016). It provides visualization of GPS locations in time and space and supplementary data in a single graphical user interface (Figure 2). It automatically keeps all the data and annotations synchronized. It has central controls to navigate in time, and a cursor in each of the visualizations to indicate the currently selected time. We use the Annotation Tool to explore data and to create or review automatic classifications.

We made the tool web-based, so it is very easy and straightforward to use with no software installation. The source code is open and can be freely used, adapted and improved by anyone. The backend serves data from UvA-BiTS¹, but can be replaced to serve data from other types of devices or sources.

For scientific collaboration, sharing results is important, so we made the visualization sharable through bookmarks. Results can be stored in files and database tables to use the annotations outside of the Annotation Tool.

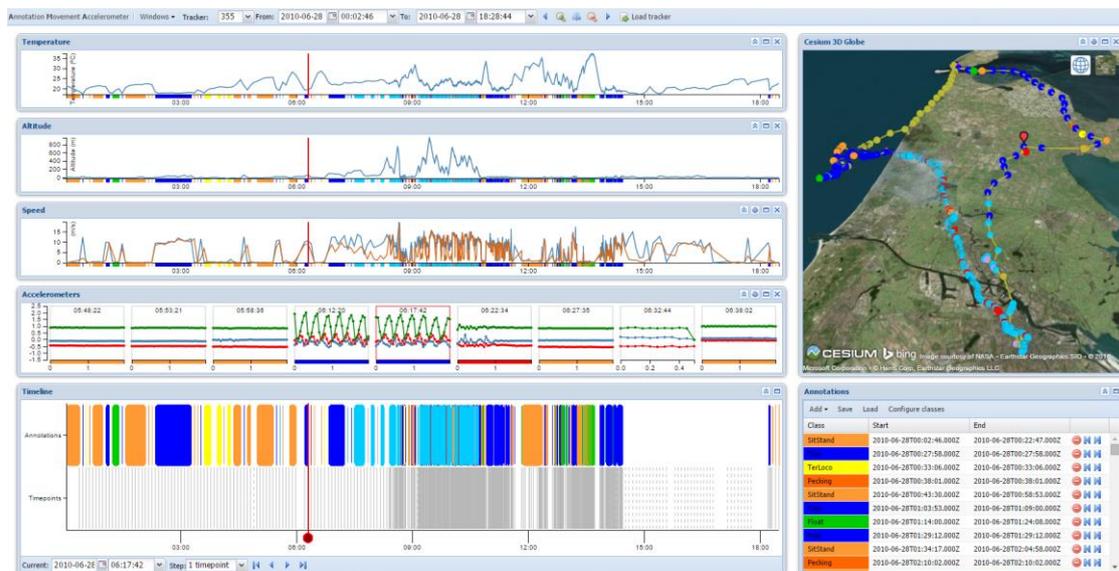


Figure 2. User interface of the Annotation Tool. The windows show from top-left, going clockwise, controls to select the device and time range, GPS fixes mapped in 3D on the globe, table of annotations, timeline with annotations, acceleration at 20 Hz, and time series of speed, altitude, and temperature.

The user interface consists of visualizations divided over windows which can be resized, moved or hidden and their states are persistent between sessions. Several windows are hidden by default for overall clarity. These are direction, change of direction and map visualization using Google maps. To visualize the acceleration, we use a row of small

¹ www.UvA-BiTS.nl

charts, where each small chart represents a single burst of acceleration data. The burst of the selected time and adjacent bursts are shown.

Some behaviours are hard or even impossible to identify using only one visualization. Combining multiple visualizations allows us to improve the interpretation of such behaviours. For example, a bird that uses orographic lift to soar at low speed and close to the ground or a bird that floats on the water surface at sea can be difficult to distinguish on the basis of speed and accelerometer alone while a land-sea mask certainly solves the problem.

2.2 Classification Tool

We developed the Classification Tool (Meijer 2016) to train models and to handle feature calculation. We added visualizations to inform the user about the training process. The tool uses ML algorithms from the Weka library (Hall et al. 2009). The Classification tool is an open source command line tool that is the process of being converted to a web application.

While many ML algorithms are available, we suggest training exploratory models using a C4.5 decision tree learner (Quinlan 1993). The model can be visualized and its decisions can be easily understood. We added an extensive visualization for this algorithm helping users to gain insight into the patterns in the dataset, and to learn which features are most valuable. Figure 3 shows an example of a model visualization.

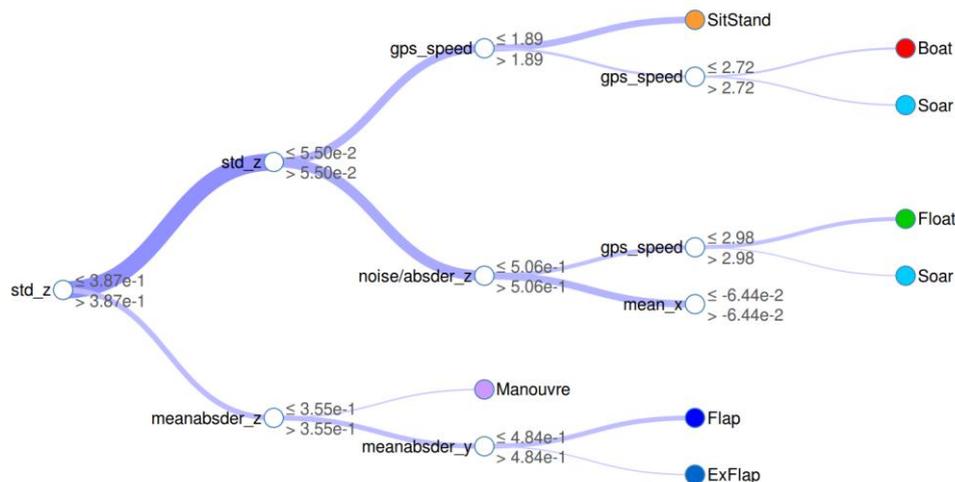


Figure 3. Trained decision tree visualization in the Classification Tool. On each node a decision is made based upon a single feature value. To prevent cluttering most of the tree is collapsed and can be expanded on demand for more detailed exploration. The width of the connections indicates the number of data records that follow that path through the decision tree.

To understand the performance of an ML model it can be validated by comparing model classifications and expert annotations. We present the results as a confusion matrix (Kohavi and Provost 1998), where rows correspond to the model's classification, and columns correspond to the expert's annotation. Each cell contains the number of classifications. To easily explore any misclassifications, we provided each cell with a hyperlink to visualizations of the corresponding misclassifications (Figure 4). Easy navigation and visualization of misclassifications is crucial for the iterative process of improving the trainset and retraining the models.

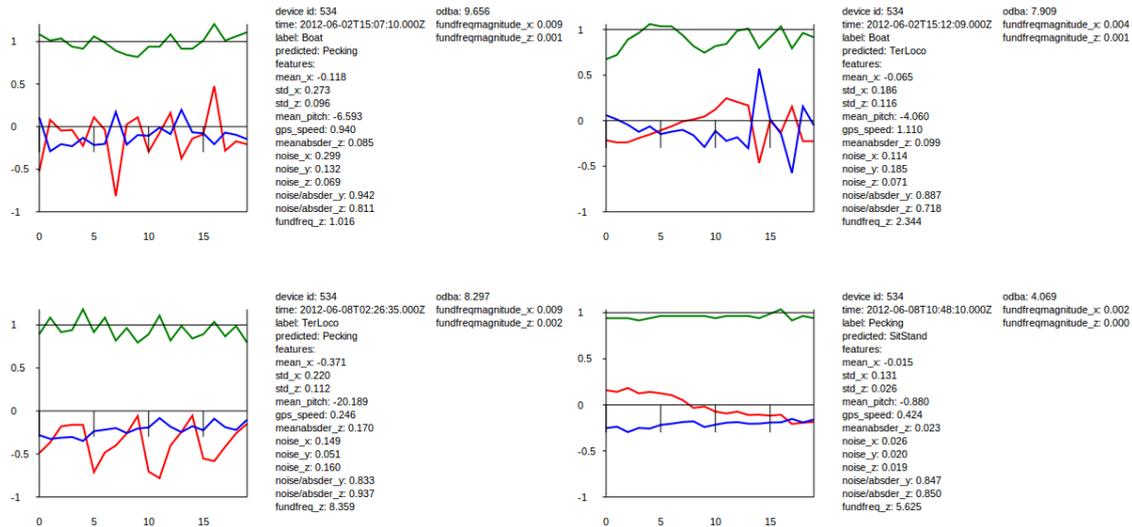


Figure 4. Visualization of misclassifications in the Classification Tool showing the accelerometer data, model’s classification, expert annotation, and feature values.

Classifications generated by the Classification tool can be loaded into the Annotation Tool described in Section 2.1 for further inspection in our integrated workflow.

3. Showcase

In this showcase, we trained a random forest (Breiman 2001) model on acceleration and instantaneous speed of manually annotated datasets of 27 individual lesser black-backed gulls as described in (Shamoun-Baranes et al in review). The behavioural classes of the model and their colour coding used by the Annotation and Classification tools are described in Table 1.

Table 1. Classes of model.

Class	Colour
Flap	Blue
Extreme flap	Dark blue
Soar	Light blue
Boat	Red
Float	Green
Sit or stand	Orange
Ter loco	Yellow
Manouvre	Violet
Pecking	Dark orange

The model automatically classified a day of tracking device data of a female lesser black-backed gull using the Classification Tool. The Annotation Tool was used for visualization as seen in Figure 2 and focused on the globe visualization in Figure 5.

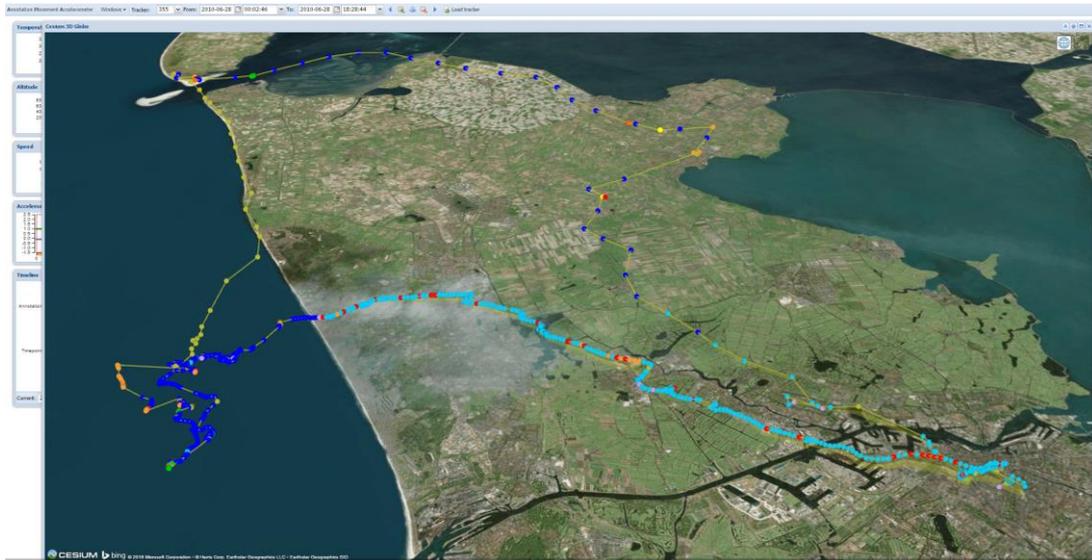


Figure 5. Globe visualization of case study inside Annotation tool.

The gull started the day at 01:03 using mainly flapping flight from her nest at Texel, an island in the North of the Netherlands, foraged on arable land on the way to the centre of Amsterdam where it arrived around 08:30. On the way it changes to soaring flight around 07:00 when the bright sun started to cause thermal lift. In Amsterdam it foraged on garbage for 2.5 hours and then, followed its way by to the coast, first soaring but switching to flapping flight again as soon as it reached the water where there is no thermal uplift. There it searched for food, rested a bit on the water and flew back along the coast to its nest on Texel where it arrived at 16:30.

During the soaring session from Amsterdam to the coast we saw some GPS points classified as 'Boat' (sitting on a boat) which are misclassifications. After investigation using the Annotation Tool, we see that the GPS point is 400m high and over land. The tri-axial acceleration for soaring and sitting on a boat are very similar. This way, we note that the model could be improved by taking the altitude into consideration.

4. Conclusions

We developed an integrated workflow that facilitates expert annotation and automated classification of bird behaviour and made it available to the UvA-BiTS community. With our tools, the users are able to visualize various data sources simultaneously, analyse the large amounts of tracking device recordings and navigate easily through the data. The ability to navigate through and analyse large heterogeneous data in a "Virtual Laboratory"², provides more insight into behaviour and improves the ability of the researcher to translate raw data into knowledge about animal behaviour. In this paper we presented a use-case to show how our toolbox is used in practice for ecological research.

Currently, a researcher needs to switch between both tools to manual annotate, train a model, perform and visualize automatic classifications. We are working towards a single web application to explore, annotate, build and apply models.

² www.UvA-BiTS.nl/virtual-lab

References

- Analytics Graphics Incorporated, 2014, Cesium: WebGL virtual globe and map engine, <http://cesiumjs.org/>
- Bom RA, Bouten W, Piersma T, Oosterbeek K, van Gils JA, 2014, Optimizing acceleration-based movement ethograms: the use of variable-time versus fixed-time segmentation, *Movement Ecology*, 2:6, <http://doi.org/10.1186/2051-3933-2-6>
- Bouten W, Baaij EW, Shamoun-Baranes J and Camphuysen KCJ, 2013, November 28. A flexible GPS tracking system for studying bird behaviour at multiple scales. *Journal of Ornithology*, 154:571-580, <http://doi.org/10.1007/s10336-012-0908-1>
- Breiman L, 2001, Random Forests, *Machine Learning*, 45(1):5-32, <http://doi.org/10.1023/A:1010933404324>
- Demšar U, Buchin K, Cagnacci, F, Safi K, Speckmann B, Van de Weghe N, Weiskopf D and Weibel R, 2015, Analysis and visualisation of movement: an interdisciplinary review. *Movement Ecology*, 3:5, <http://doi.org/10.1186/s40462-015-0032-y>
- Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P and Witten IH, 2009, The WEKA data mining software. SIGKDD Explorer Newsletter Association for Computing Machinery, 11(1):10-18, <http://doi.org/10.1145/1656274.1656278>
- Kays R, Crofoot MC, Jetz W and Wikelski M, 2015, Terrestrial animal tracking as an eye on life and planet. *Science* 348 (6240). <http://doi.org/10.1126/science.aaa2478>
- Kohavi R and Provost F, 1998, Glossary of Terms, *Machine Learning*, 30:271-274, <http://doi.org/10.1023/A:1017181826899>
- Meijer C, 2016, eEcology-Classification: v1.1.2. *Zenodo*, <http://doi.org/10.5281/zenodo.44665>
- Quinlan R, 1993, C4.5: Programs for Machine Learning, Morgan Kaufmann, San Mateo, US
- Resheff YS, Rotics S, Harel R, Spiegel O and Nathan R, 2014, AcceleRater: a web application for supervised learning of behavioral modes from acceleration measurements. *Movement Ecology*, 2:27, <http://doi.org/10.1186/s40462-014-0027-0>
- Shamoun-Baranes J, Bom R, Van Loon EE, Ens BJ, Oosterbeek K and Bouten W, 2012, From Sensor Data to Animal Behaviour: An Oystercatcher Example. *PLoS ONE*, 7(5): e37997, <http://doi.org/10.1371/journal.pone.0037997>
- Shamoun-Baranes J, Bouten W, Van Loon EE, Meijer C, Camphuysen CJ, 2016, Flap or soar? How a flight generalist responds to its aerial environment. submitted for publication
- Verhoeven S, 2016, eEcology Annotation tool: v1.1.3. *Zenodo*, <http://doi.org/10.5281/zenodo.45200>