

Behavior Classification of Dairy Cows Fitted with GPS Collars

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Abstract. Precision management systems for livestock offer the potential to monitor and manage animals on an individual basis. A key component of these sensor based systems are the analytical models that automatically translate sensor data into different behavioral categories.

Here we consider the use of GPS data for modelling the behaviour of dairy cows. The performance of this approach is validated across a study involving 24 Holstein-Friesian dairy cows that were each fitted with a GPS unit on a neck collar. The behavior of the cows are classified into 4 general classes: grazing; moving from paddock to paddock; milking; and resting. Using simple rules derived from prior information about the behavior of dairy cows, and information about the layout of the farm, the classification was substantially improved.

The utility of a log of animal behaviour will increase when joined with other data (milk yield, for example) and has the potential to provide useful in animal management, obtained at little cost.

Keywords: Behavior classification · Machine learning · Livestock · Precision management · Geographical positioning system, GPS

1 Introduction

Precision management of livestock differs from traditional herd management by tailoring decisions to the individual animal. The aim of precision strategies is to maximize the potential of each animal and ensure resources are allocated efficiently on the farm. An animals behavioral interactions with its physical environment must be continuously monitored for precision management strategies to be successfully implemented. The observed behaviors of each animal must then be linked to management knowledge in areas such as breeding, welfare and nutrition to enable the appropriate action to be taken. For instance, illness can be predicted in cattle when there is a reduction in the level of social interaction or rumination and feed intake [4, 13]. Furthermore, other behavioral changes have been shown to be indicative of when cattle are: lame [10]; in estrus [1, 2]; in pain [7]; or under heat stress [3].

Sensors and digital technologies are becoming an important enabler for precision livestock management. Sensor based monitoring systems offer the potential for continuous and autonomous monitoring of cattle without the need for human involvement. Such systems generally consist of a sensor or suite of sensors that are fitted to each animal and a model that uses the sensor data to infer the animals behavior. Commercial monitoring systems classify the basic behaviors of a cow, but most importantly, compare the classified behaviors to rules regarding the animals expected or normal behavior in order to alert to potential management issues [1, 2, 4].

Here we consider the use of GPS data for modelling the behaviour of dairy cows. The performance of this approach is validated across a study involving 24 Holstein-Friesian dairy cows that were each fitted with a GPS unit on a collar around their neck.

We have GPS data, collected every 10s, on the 24 cows over a 14 day period from 27/11/2012 to 10/12/2012. The cows are part of a single herd of 300 animals on a farm located in the north-east of Tasmania.

In some instances (111 animal days) the GPS record is complete for an animal over a 24h period. In others (136 animal days) it is only a partial record that may or may not contain usable information. We have behavioral data collected by observers for brief periods during the 14 day period. However, the data was found to cover too brief an interval, was often recorded at very short intervals (2s) and covered too many activities (chewing, resting with head up, etc.) to be usefully matched to GPS records.

Instead we have explored several other options. We have investigated unsupervised segmentation techniques that have been applied to GPS trajectories collected from wild animals [6]. These are shown to have some utility in interpreting the trajectories.

We have also investigated classifying a limited number of trajectories by eye, relying on domain knowledge of the behavior of dairy cows. We can then use these trajectories as data to train a classifier. Hence we are automating a process of information extraction that could be done more laboriously by the farmer.

In addition we have used a number of heuristic rules to improve the classification. We find that, using a classifier and several simple heuristic rules, it is possible to classify the animals behaviour into 4 broad classes, that is: milking (at the milking sheds); moving from paddock to paddock; grazing; and resting.

2 Methods

2.1 Cattle Collar Instrumentation

The behavior monitoring collars [12] fitted to the dairy cows were comprised of a 20-channel GPS receiver chip, an active GPS antennae, a microcontroller and 915 MHz transceiver, a 4 GB micro SD card for data storage and a Honeywell HMC6343 compass module containing a 3-axis MEMS accelerometer and a 3-axis magneto-resistive (magnetometer) sensor. The compass module of the behavior monitoring collars acted as an Inertial Measurement Unit (IMU).

The IMU was ignored as the focus of this particular study was upon classifying cattle behavior using the GPS. The effective battery life was approximately 14 days. After retrieval of the collars at the end of the data collection period, the memory storage cards were removed and the data downloaded and converted from binary format.

2.2 Segmenting a Trajectory into Segments Characterized by a Homogeneous Behaviour 1

Calenge (2006) describes an approach to the segmentation of movement data into homogeneous segments. The method relies on a Bayesian partitioning of a sequence and was originally developed for partitioning DNA sequences [8].

Suppose that the steps, the distances between successive locations, have been independently generated by Gaussian distributions, with different means corresponding to different behaviours. We generate $d = 1, \dots, D$ models with different means. Based on these *a priori* models we estimate both the number and the extent of the segments building up the trajectory.

Given an optimal k -partition of the trajectory, if the i^{th} step of the trajectory belongs to the segment k predicted by the model d , then either the move $i - 1$ belongs to the same segment, in which case the segment containing $i - 1$ is predicted by d , or the move $i - 1$ belongs to a different segment, and the other $(k - 1)$ segments together constitute an optimal $(k - 1)$ partition of the trajectory $[1 : (i - 1)]$.

Calenge (2006) uses a range of equally spaced means across the observed range of the steps, with a common variance. We suspect that the means of the behaviors we are interested in are not equally spaced and have differing variances so we fit a mixture of 4 Gaussians using the EM algorithm. For the trajectory of animal 6 on day 2 (Fig. 1) we get the 4 distributions, plotted in Fig. 2.

Figure 3 shows the sequential step lengths. The mean of the Gaussian that best models each segment is shown by a horizontal bar. Figure 4 shows the segmented trajectory.

2.3 Segmenting a Trajectory into Segments Characterized by a Homogeneous Behaviour 2

Calenge [6] also describes a method of

- calculating the residence time for each location on the trajectory;
- use the method of Lavielle [9] to partition the trajectory.

The method of Lavielle finds the best segmentation of a time series, given that it is built by K segments. It searches the possible segmentations for one in which the difference between the observed trajectory and the model is minimized. Let Y_{t_i} be the value of the variable (e.g. residence time, although other variables are possible) at time t_i . We suppose that the data have been generated by the following model:

$$Y_{t_i} = \mu_{t_i} + \sigma_{t_i} \epsilon_{t_i}$$



Fig. 1. The trajectory of animal 6 on day 2.

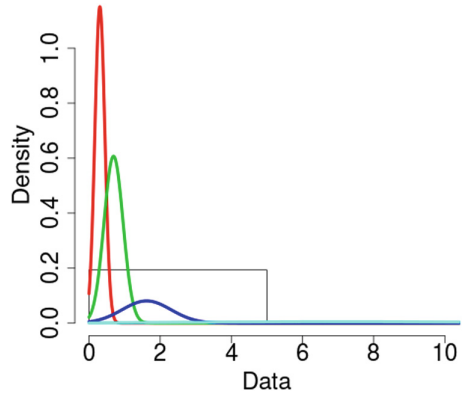


Fig. 2. The mixture of Gaussians fitted to the distances for Animal 6, day 2.

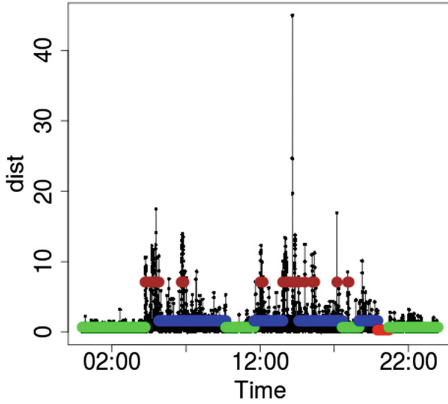


Fig. 3. The sequential step lengths. The mean of the Gaussian that best models each segment is shown by a horizontal bar.

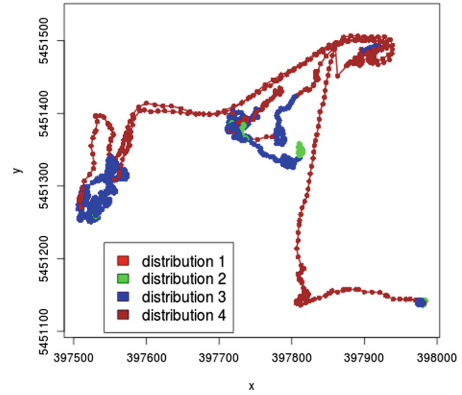


Fig. 4. The segmented path for animal 6 on day 2 using the method of Sect. 2.2.

where μ_{t_i} and σ_{t_i} are the mean and standard deviation of Y_{t_i} . ϵ_{t_i} is a sequence of zero mean random variables with unit variance, not necessarily independent.

We use the most general model, assuming that (writing t_i as i) μ_i and σ_i can both vary between segments, but are constant within a segment. For a given partition of the series built by K segments with known limits, the following function can be used to measure the discrepancy between the observed trajectory

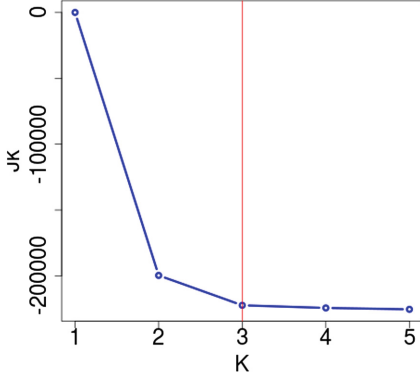


Fig. 5. A plot of $J(K)$ versus K indicates that 3 segments will minimize $J(K)$. Subsequent segments add little to the reduction in the value of $J(K)$.

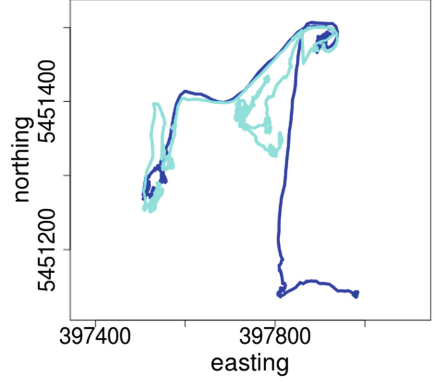


Fig. 6. The segmented path using $K = 4$ with the method of Lavielle [9].

and the model:

$$J_k(Y) = \sum_{k=1}^K G_k(Y_{i,i \in k}),$$

where

$$G_k(Y_{i,i \in k}) = \frac{1}{n(k)} \log \left(\frac{1}{n(k)} \sum_{i=t_1^k}^{t_{n(k)}^k} (Y_i - \bar{Y}_k)^2 \right)$$

where $n(k)$ is the number of steps in segment k . The method of Lavielle uses a dynamic programming algorithm to find the best segmentation of the trajectory, i.e. the segmentation for which $J_k(Y)$ is minimized. The optimal number of segments K is a parameter in the model and [9] suggest plotting $J(K)$ versus K to see if there is a clear “break” at an optimal value of K . Figure 5 shows this plot for animal 6, day 2, and Fig. 6 shows the resulting segmentation into 3 classes.

2.4 Classification Based on Derived Variables from Fixed Time Segments

We take the 10s spaced location data and summarize it to longer segments. We derive a number of variables from each segment:

- the distance between the starting point and the end point of the segment;
- the total distance travelled in the segment;
- the max movement in any 10s segment; and
- the maximum difference in movements between 10s segments.

We selected 5 animals on single days as the training data set (animal 21 on day 1, etc.) and 5 other animals/days as the test data set (animal 6 on day 1, etc.). The trajectories of these animals were manually segmented into the 4 classes milking; moving, grazing and resting, using knowledge of the layout of the farm and animal behaviour.

Take, for example, the partial trajectory (from 07:00 to 17:00) of animal 21 on day 1, shown in Fig. 7. Figure 8 shows the same trajectory as distance from an arbitrary origin at the milking sheds. We can segment it into the following sequential behaviours;

- time at the milking shed.
- movement to a grazing paddock (paddock 1);
- grazing;
- movement to the milking sheds;
- time at the milking shed;
- movement to a grazing paddock (paddock 2);
- grazing.

This divides the animals behavior into 3 classes: milking; moving; and grazing, as shown by the trajectory color in Figs. 7 and 8. For this trajectory there was no resting class.

The derived variables were calculated and a linear discriminant analysis was used to classify the segments. The classification was then tested on the 5 test animals. Segment length of 2, 5 and 10 min were tried with overall classification accuracies of 0.58, 0.58 and 0.61.

See Fig. 9 which shows the classified trajectory for one of the test animals (animal 6 on day 1) using segments of 10 min duration.

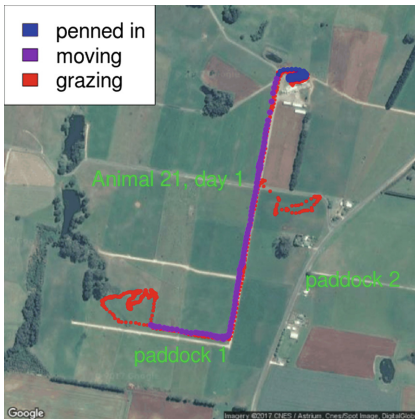


Fig. 7. Animal 21, day 1. Segmented into three classes: penned in (at the milking shed); moving and grazing on the basis of knowledge about the farms practice.

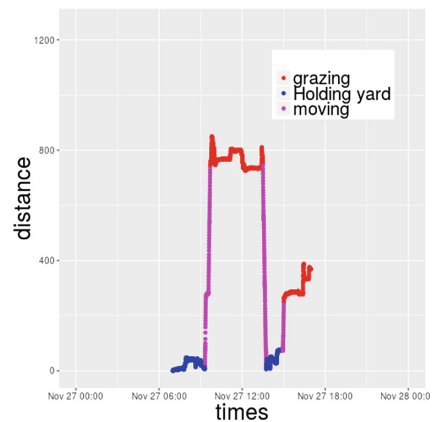


Fig. 8. The trajectory for animal 21, day 1 (Fig. 7) as distance from an arbitrary origin at the milking sheds.

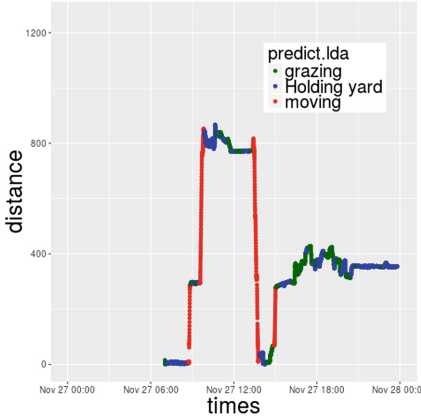


Fig. 9. A classified trajectory for Animal 6, day 1

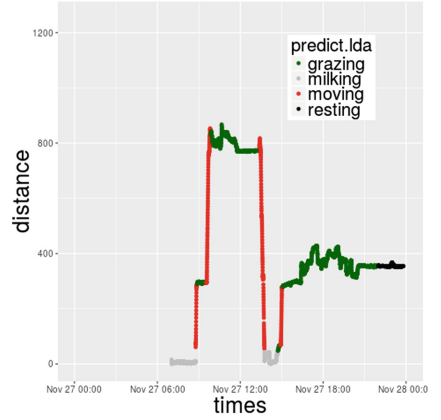


Fig. 10. A classified trajectory (Fig. 9) after the application of the two heuristic rules.

2.5 Heuristic Rules

We have some prior information about the movement of dairy cows. It is suggested in [5] that:

- grazing occupies about 8 (dairy cows) to 9 (beef cattle) hours a day;
- ruminating occupies about 6 h a day (see also [14]);
- cattle lie down to sleep, ruminate or drowse for nearly half of their day.

In addition we know the layout of the farm and can inspect the typical movements of various animals. This leads us to 2 simple rules:

- the location of the milking shed is fixed and there appears to be no grazing area around it (animals seem to be closely bunched together before milking). We can geo-fence the milking sheds and any time spent in that area can be classed as “milking” time;
- dairy cows do not graze at night. The time between 22:00 and 04:00 (a period when the GPS record shows no more movement than can be attributed to GPS inaccuracy) can be classified as “resting” which includes: resting; sleeping; and ruminating.

Using these simple rules we can improve the behaviour classification. Figure 9 shows a classified trajectory (using the method of Sect. 2.4) and Fig. 10 shows the same classified trajectory after the application of these heuristic rules.

3 Results

We have tried both segmentation and classification methods on this data. The segmentation of GPS paths appears in the ecology literature where two features are apparent:



Fig. 11. A classified trajectory for Animal 6, day 2. This animal was not included in either the test or the training data. The trajectory has been cleaned up with the two heuristic rules.

- the location of the animal is interesting information in itself;
- it is likely that training data is unavailable as direct observation of the animal over an extended period may not be possible.

We have a somewhat different situation. We have some prior knowledge about the behaviour of the animals at different times and locations. We can use this knowledge to both produce and evaluate the classified trajectories. Our problem is to automate this process. Consider the following three segmentations of the same trajectory (animal 6 on day 2):

- Figure 4, the Gueguen segmentation. This has separated moving and grazing. There are occasional rest periods mixed with the grazing. However, the overall segmentation is not unreasonable;
- Figure 6, the Lavielle segmentation into 4 classes. It has separated moving from everything else but has not successfully segmented the other classes;
- Figure 11, an animal classified on 10 min segments, not included in either test or training data. The classification combined with the heuristic rules has made the trajectory quite interpretable.

The classification method appears to perform better than the segmentation methods. This may be due to the fact that is based on the 5 derived variables which give more information than the successive positions.

4 Discussion

We anticipate that the GPS data will only be able to separate the behaviour into a small number of distinct activities. Clearly, GPS information will not let us distinguish between sleeping, drowsing or ruminating. In addition the continuous small errors in GPS readings may make a stationary animal indistinguishable from a slowly moving one. This will cause some confounding of resting (Fig. 12) and grazing (Fig. 13). Both trajectories fail the Wald-Wolfowitz runs test [11] for randomness, although we suspect that only the resting (Fig. 12) trajectory is in fact random noise.

The segmentation achieved by the Gueguen method (Fig. 4) appears reasonable. It appears that the class with the smallest mean does not cover the milking. There are times in the grazing paddock when the animal is more consistently stationary than in the milking shed. However, the segmentation is relatively easy to align with our prior knowledge of the animals behavior.

The Lavielle method suggests 3 behavior classes (Fig. 5). We have selected 4 classes for an easier comparison with other methods. However the resulting segmentation (Fig. 6) make little sense.

Using the ten minute segments (Sect. 2.4) gives us a reasonable classification, shown in Fig. 9.

Table 1. Summary of the grazing behavior of Animal 6 and 29.

	Animal 6		Animal 29	
	Time (minutes)	Distance (meters)	Time (minutes)	Distance (meters)
27/11/12	676.83	4327.20	601.17	3925.46
28/11/12	892.67	4779.78	759.33	4345.09
29/11/12	908.33	4759.01	774.00	4102.31
30/11/12	796.00	4855.96	675.00	3918.92
01/12/12	820.17	4810.77	696.17	3199.86
02/12/12	857.00	3868.14	738.33	3392.88
03/12/12	836.17	5227.78	699.00	3853.94
04/12/12	839.67	5098.36	725.17	3990.13
05/12/12	847.00	5536.96	738.33	4155.51
06/12/12	857.33	5047.15	726.50	3507.63
07/12/12	885.00	4323.86	359.33	1952.70
08/12/12	242.67	783.91	250.17	1164.36
09/12/12	NA	NA	466.17	2508.31

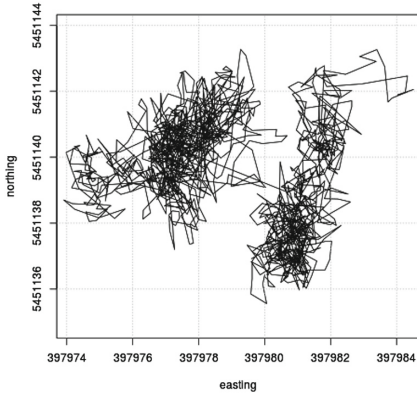


Fig. 12. Animal 6, day 2 from midnight to 04:15. We assume that the animal is resting.

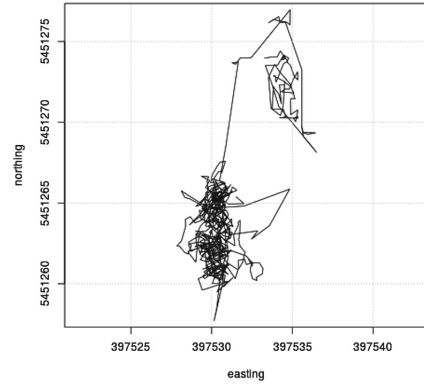


Fig. 13. Animal 6, day 2 from 9:30 to 11:15, the animal is grazing

Using the method of Sect. 2.4 and two simple heuristic rules we can produce an acceptable classification of the GPS trajectory of a dairy cow into the 4 classes: milking, moving, grazing and resting. Using the classification we can produce a summary of time spent grazing and distance covered for each animal in the sample. This is given in Table 1 for animals 6 and 29.

The information derived from the classified trajectories has a number of potential uses. By itself it may indicate individual animals that are not moving well. It may also indicate some features of herd behaviour, including different spatial behaviour in different paddocks.

Its utility will increase when joined with other data (milk yield, for example) to produce a summary useful in animal management. These methods have the potential to yield important and useful information for animal management at quite a low cost.

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