Animal behaviour analysis with GPS and 3D accelerometers

A. Spink[1], B. Cresswell[2], A. Kölzsch[3], F. van Langevelde[4], M. Neefjes[3], L. P.J.J. Noldus[1], H. van Oeveren[4], H. Prins[4], T. van der Wal[5], N. de Weerd[4] and W. Frederik de Boer[4]
[1]*Noldus Information Technology BV, Nieuwe Kanaal 5, 6709 PA Wageningen, The Netherlands*
[2]*Biotrack Ltd, 52 Furzebrook Road, Wareham, Dorset, BH20 5AX, United Kingdom*
[3]*Project Group Movement Ecology and Department of Animal Ecology, Netherlands Institute of Ecology (NIOO-KNAW), Droevendaalsesteeg 10, 6708 PB Wageningen, The Netherlands*
[4]*Wageningen University, - Resource Ecology Group, 6708 PB Wageningen, The Netherlands*
[5]*AeroVision BV, Bussummerstraat 3, 1411 PK Naarden, The Netherlands*
Andrew.Spink@noldus.nl

Abstract

A herd of dairy cows were equipped with GPS tracking collars and at the same time, their behaviour was manually scored with Pocket Observer software. TrackLab was used to visualize the data. The manually scored behaviours were used to classify the GPS data, and for foraging, resting and walking, the GPS data had a very high predictive value for the behaviours. Although ruminating and standing could not be distinguished on the basis of GPS data alone, a further experiment on Canada Geese indicated that the addition of accelerometer data to the GPS tags showed very promising results with respect to distinguishing more behaviours than could be classified using GPS alone. This opens up a spectrum of possibilities for farm mangers including automatic detection oestrus in cattle and geofencing applications.

Keywords: GPS, Tracking, Cows, Geese, Goose, 3D Accelerometer, Behaviour detection

Introduction

The spatial movement patterns of individual animals have much to tell us about their behaviour, physiological status and wellbeing. Therefore tracking animals with Global Navigation Satellite Systems (GNSS), of which the GPS is the most commonly used, has become an important research method for studying wildlife behaviour and how human activities affect this behaviour. Feeding, fleeing and resting for instance each have specific spatial and temporal patterns. To study more detailed behaviour, the spatial and temporal resolution of the GPS must be of high accuracy. One way of improving the standard GPS spatial accuracy is the use of EGNOS, a European augmentation system that improves GPS positioning to within 1 meter. The FP7 financed project ETrack (www.etrack-project.eu) develops an integrated system for animal tracking and behaviour analysis. It is using the EGNOS augmentation system to GPS positioning. The objective of E-Track is to better and more reliably track and analyse the movements and behaviour of animals under field conditions. The E-Track system develops data acquisition systems (collars for mammals, backpacks for birds) with GPS + EGNOS receivers and optional 3D accelerometers, data communication systems. The data is transferred in real-time (or another mode if desired) to the analysis and visualisation software. Here, the high accurate positioning and movement data are processed and analysed. The E-Track project aims to develop an end-to-end system for movement tracking and behaviour recognition based on GNSS (Global Navigation Satellite System) telemetry, with high temporal and spatial resolution, sufficient to enable the fine-scale measurement of behaviour and interactions of wildlife.

The use of GNSS collars in animal movement research is growing. An inventory of scientific publications shows that the number of publications in which researchers track the position of animals by a satellite system has been steadily growing since 2006, and still does. 56% concerns publications about tracking wildlife; 17- 22% concerns publications about tracking livestock (personal communication, Albert Willemsen (Noldus) Feb. 2013).

In addition to animal studies and research, the use of GNSS in livestock management has been suggested for applications in animal monitoring (oestrus and illness detection), movement and pasture use (grazing patterns), herd location (free range cattle) and virtual fencing. Barriers for further operationalisation involve the costs of the collars and the power supply to the devices, in particular in comparison to pedometers and close range sensors.

This paper presents two experiments carried out to investigate the possibility of behavioural classification of animals using GPS data. It is known that GPS data can be used to derive certain behavioural data, but also there are limits to the resolution of similar behaviours and it has been suggested that if GPS data is supplemented with accelerometer data, a finer resolution of behaviours might be possible (Anderson *et al.* 2012). These experiments explore those boundaries. In the first experiment, cows were equipped with an EGNOS-enabled GPS collar and behaviour was classified based on manually scored observations with event-logging software. In the second experiment, accelerometers were integrated with GPS tags and attached to Canada Geese whilst their behaviours were manually logged. The accelerometer data was then compared with the manually scored behaviours.

Materials and Methods

Livestock experiment

This experiment was carried out at two locations. The first was on a pasture of a dairy farm near the village of Bennekom in the east of The Netherlands (52°01' N, 5°62' E). It was a rectangular field with a line of trees on the north side and freely available water plus silage for additional feeding. The second experiment took place in a partially wooded area in the same district (52°01' N, 5°75' E). This site also had water available, and a strip of grassland.

Nine cows (Fresian Holstein) in the first part and 8 in the second were fitted with Lotek EGNOS-enabled GPS collars (GPS6000M from Biotrack, Wareham, UK). They were tracked for ten days spread over three weeks at a variety of sample rates.

The behaviours of the cows were manually scored during 15-minute observations using event-recording software (Pocket Observer 3.1 from Noldus Information Technology, Wageningen, The Netherlands) installed on handheld computers (Psion Workabout) and analysed with The Observer XT 11 (Noldus Information Technology, Wageningen, The Netherlands). The ethogram used was shown in Table 1 (below).

The GPS data were visualized with TrackLab 1.0 (Noldus Information Technology). The dehabitatLT package in R (Calenge, 2006) was used for calculating distance and turn angle. A permutation ANOVA test using the lmPerm package in R (Wheeler, 2010) as conducted to test whether distance and turn angle differed significantly between behavioural types and therefore were likely to be useful in the creation of decision rules to classify the data into behavioural groups. When the permutation ANOVA indicated a significant difference for either distance or turning angle between the behavioural classes, the same test was carried out pairwise on all combinations of behaviour as a post-hoc test (Basso *et al.* 2008) with Bonferroni correction (Zolman, 1993). Decision trees using the CART (classification and regression tree) method (Nathan *et al.* 2012; Lewis 2000) were used to calculate how much of the data could be correctly classified based on thresholds of distance moved and turn angle.

Table 1. Ethogram of cow behaviour

Behaviour	Description
Walking	Movement from one location to another without the head orientated at the ground
Foraging	Grazing or browsing taking frequent bites of forage
Standing	Standing still, no movement to another place
Ruminating	Cow is lying down
Drinking	Drinking at the water supply near the stables
Grooming	Cleaning or scratching itself
Social	Interaction with other cows (e.g. grooming, mounting)
Dry Forage	Consuming silage left by the farmer

<u>Accelerometer experiment</u>
Six Atlantic Canada geese (*Branta canadensis canadensis*) were fitted with GPPP GPS and accelerometer tags from Biotrack (Wareham, Dorset). The Biotrack GPPP platform contains a u-blox GNSS receiver, 3D accelerometer IC, microcontroller and microSD card memory. It is programmed to log location data simultaneously in two formats: NMEA locations and raw data. The NMEA solution uses ionospheric and other correction factors via EGNOS if a satellite can be acquired. It calculates a location using Precision Point Positioning (PPP), which provides more accurate results by incorporating carrier phase measurements. Raw data provides a means to achieve the same results by post-processing as well as other solutions such as alternative Kalman filters. Data from the accelerometer comprised all three axes sampled at a rate of 30-50 Hz (three readings: X,Y,Z).

The experiment took place in an experimental field of 26 x 26 m at the Netherlands Institute of Ecology (NIOO-KNAW) in Wageningen, The Netherlands. The tags were less than 2% of the body weight of the geese and were mounted on the animals using a backpack. The behaviours of the geese were scored and analysed with The Observer XT 11 (Noldus Information Technology, Wageningen, The Netherlands). They were also filmed with a video camera. The ethogram used is shown in Table 2.

Table 2. Ethogram of Canada Goose behaviour

Behavioural types	
Standing	Running
Walking	Flapping the wings
Sitting	Calling
Feeding while standing	Stretching
Feeding while walking	Shaking
Feeding while sitting	Looking (stretching the neck)
Drinking	Sleeping
Preening	Interaction
Pecking/preening the tag or ring	

The accelerometer and behavioural data was plotted and analysed visually.

Results and Discussion

GPS Tracking of cows

The GPS tracking devices together with TrackLab visualization gave useful information about the spatial and temporal activities of the cows. As can be seen in the figures below, the cows spent relatively more time in the locations where silage and water were available and when they were moving to the far end of the field, they tended to move at higher velocities than when they were nearer to the farm buildings.

Behavioural classification

To find out how distance and turning angle between GPS fixes are related to behaviour these two movement metrics were plotted against each other for the four dominant types of behaviour (Fig. 3).

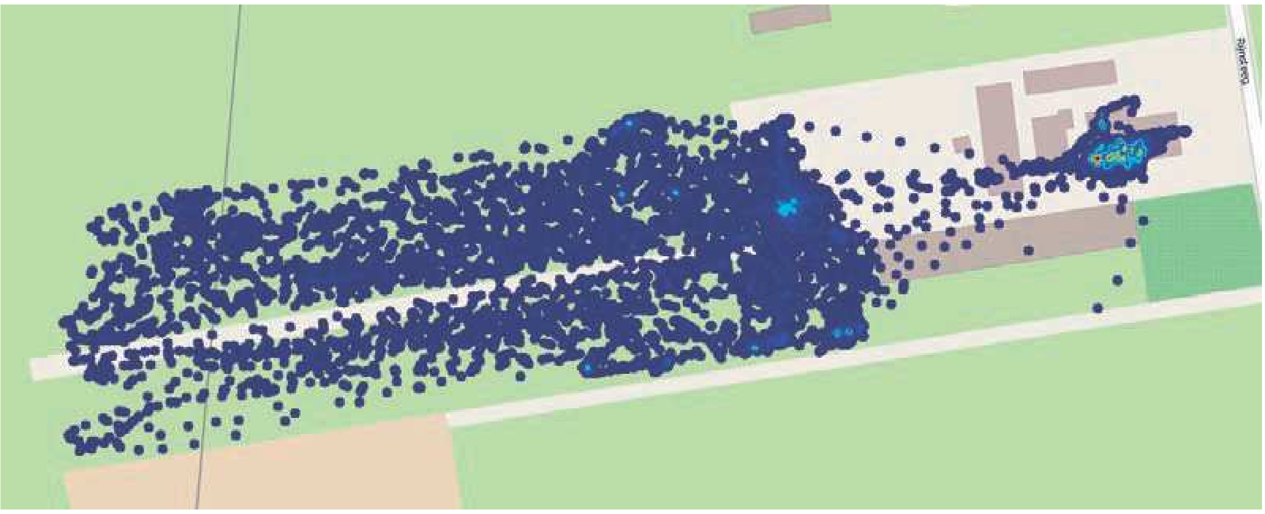

Figure 1: Visualization of GPS tracks of 9 cows in TrackLab from one day. The heat map is generated according to the density of the GPS samples. It can be seen that the cows spent a relatively large amount of time in the stall (on the right), and near the silage and water (in the centre) and that when in the field they spent less time at the far end of the field than nearer to the farm buildings.

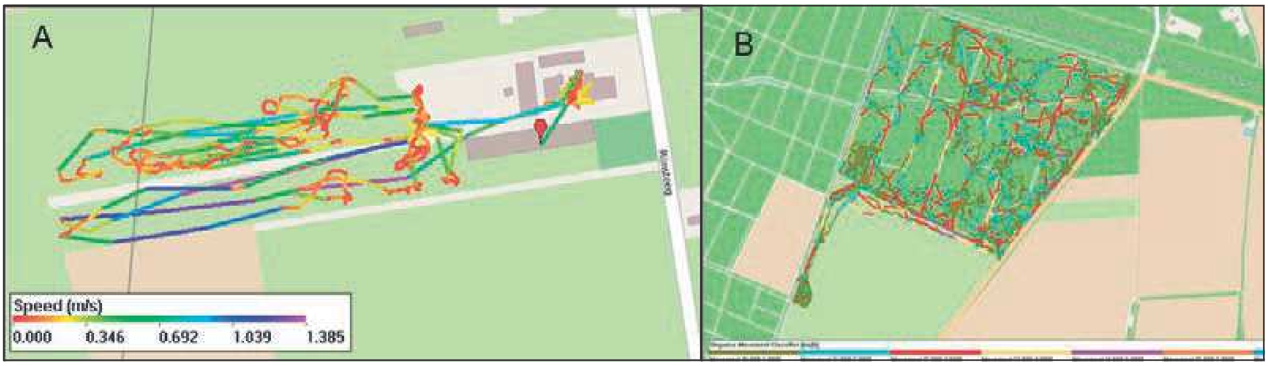

Figure 2: Visualization of a single GPS track of a cow in TrackLab from one day. The colour of the line indicates the speed of the cow at that moment. A) At the farm pasture. It can be seen that the cow is moving slower in the region next to the farm buildings where the water and silage were available. B) At the wooded site. Searching behaviour (long flights, high speed) can be distinguished from foraging behaviour (short flights, low speed).

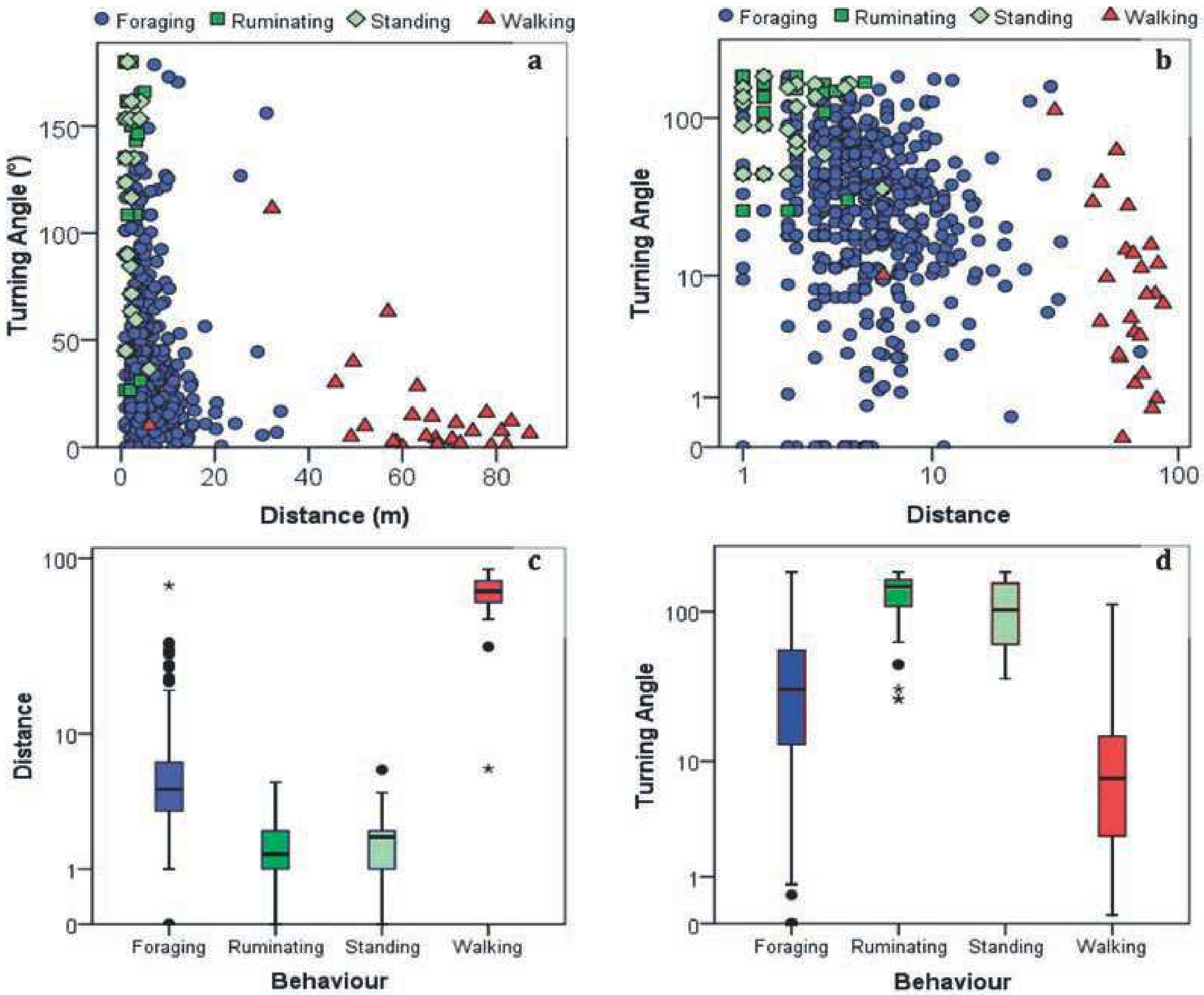

Figure 3. a), b), Relationship between turning angle and distance for each of the four dominant types of behaviour on both a linear and logarithmic scale. c, d) Boxplots show the distribution of both distances and turning angles for the different groups of behaviour. Letters on top of the graphs depict if there are significant differences for these movement metrics between the groups based on permutation ANOVA tests.

Walking can be distinguished most clearly because the distance covered between GPS fixes during the 1 minute sample interval is much larger than for the other types of behaviour and the turning angle for Walking is relatively low. Foraging was the most variable behaviour, with large variations in both distances and turning angles. Ruminating and Standing are related to small distances as expected, but both types of behaviour include turning angles varying from 0 to 180 degrees. A permutation ANOVA showed that both distance ($F_{3.603}=782.46$, $p<0.0001$) and turning angle ($F_{3.593}=95.77$, $p<0.0001$) differed significantly between groups. All behavioural classes were found to be significantly different from each other except for Ruminating and Standing.

A decision tree was then created which formed the model for validation. The data used to form the model was able to correctly classify 93.4% of the data. This was then validated with the other half of the dataset resulting in 87.5% overall correct classification. However, standing was only classified correctly 9.5% of the time, mostly being classified as foraging instead (Table 3).

If standing and ruminating were combined together as one behaviour ('resting') then the percent samples correctly classified as resting in the training and validation datasets were 78.7% and 62.9% respectively.

Table 3: Confusion matrix for the decision tree for the behaviours in the training and validation samples, based on movement and turn angle. The numbers are numbers of samples and the diagonal (in bold) shows the correct classifications.

Result Training Sample					
Observed	Predicted				Percent Correct
	Foraging	Ruminating	Standing	Walking	
Foraging	**498**	7	0	1	98.4%
Ruminating	8	**41**	0	0	83.7%
Standing	12	10	**4**	0	15.4%
Walking	2	0	0	**24**	92.3%
Overall Percentage	85.7%	9.6%	0.7%	4.1%	93.4%
	Result Validation				
Foraging	**443**	19	5	3	94.3%
Ruminating	21	**33**	1	0	60.0%
Standing	26	12	**4**	0	9.5%
Walking	**0**	0	0	**42**	100%
Overall Percentage	80.5%	10.5%	1.6%	7.4%	85.7%

GPS and Accelerometer data from geese

Although the accelerometer data have not yet been statistically analysed and classified, it is clear from plots of the data (see Fig. 4 for an example) that they give significant extra information. Whereas the GPS data for the cows were unable to be used to distinguish between ruminating and standing, the accelerometer graphs shows a clearly different waveform for the sitting compared with feeding while sitting. Although of course this must be a tentative conclusion, as it is not yet statistically verified, it is clear that this is a very promising technique.

Future developments

The requirements towards a telemetry system are always rising, asking for an even higher spatial resolution. The measuring of the movements is no more the only target of interest; additional physical, physiological, pathological, etc. data are requested from automated telemetry systems. Sensors collecting information about temperature, light and acceleration are used in frequently to receive important information from the animal investigated. The additional data from the 3D accelerometer enriches the movement data and provides information on detailed behaviour. Depending on where the accelerometer is attached to the animal (i.e. the leg, the back or the neck) it reveals specific movement behaviour. For instance attachment of a 2D accelerometer to the neck provides insufficient information to separate between standing and lying (De Mol, 2009). Additional to the GNSS and 3D Accelerometer the use of 3D magnetometers is interesting. This provides information on the position of the sensor relative to both gravity and magnetic field. At its simplest level, this can tell which direction the cow is facing, for example.

A logical consequence of the use of sensors, in particular the accelerometers, is the huge amounts of data, that must be stored, transferred and analysed. An option is to apply data reduction on board, for instance to measure tilt angle. At this stage, the wealth of information coming from the accelerometers suggests better use than calculating tilt angle.

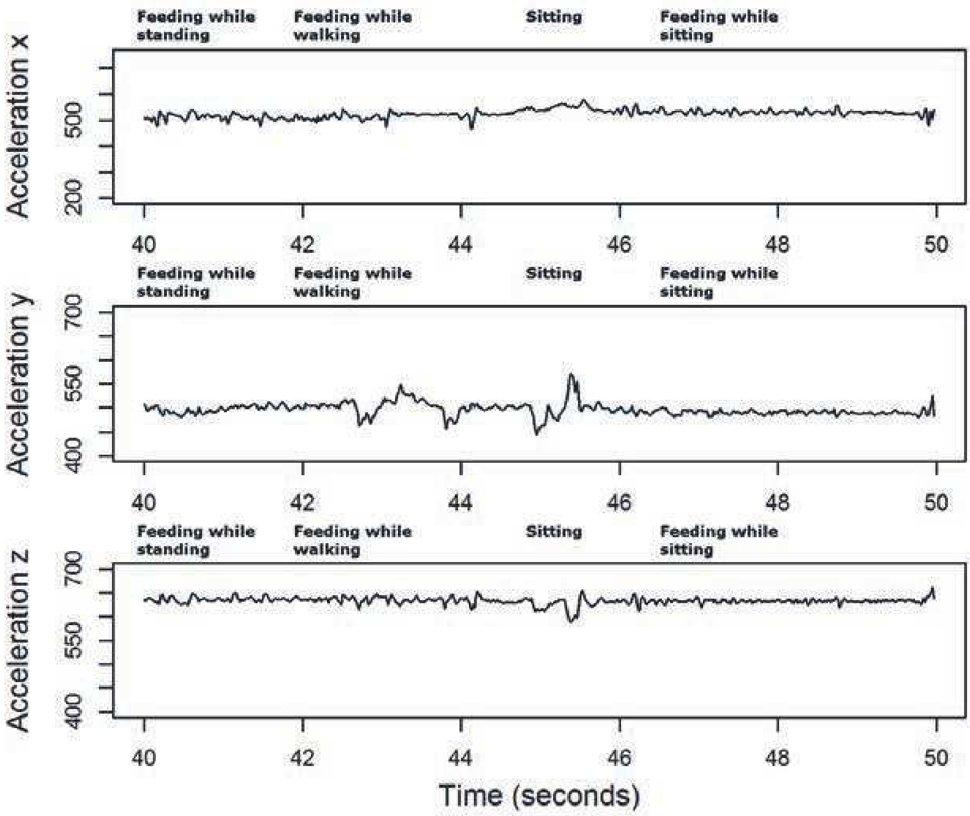

Figure 4. Accelerometer data for Canada Geese plotted against manually scored behaviours. The behaviours started at the time indicated by the first letter of the behaviour name.

Although the GPS data could not distinguish between certain behaviours, it is possible that with application of techniques such as better smoothing of the data (for example using the outlier removal and weighted least square smoothing available in TrackLab), and increased precision using EGNOS Data Access Service (EDAS; Liu *et al.* 2012), some more behaviours will be able to be distinguished. However, the preliminary accelerometer data indicate that a combination of GPS and accelerometer data is probably the most promising route for behavioural detection.

Once it is possible to automatically detect the behaviours in cattle, a range of new possibilities is opened up. Researchers will be able to gain much more detailed information about their experimental animals. Farmers will be able to use this information to improve the efficiency of their husbandry, especially if the data were coupled to a real-time feedback and decision-making software. For instance dairy cows in oestrus show deviating behaviour such as raised levels of movement, being more restless and more interactive with other cows (Walton & King, 1986; Løvedahl & Changunda 2010). The use of GNSS and 3D accelerometer data can be an addition or improvement to existing systems.

Another application which this sort of data could be applied to would be intelligent geofencing. Geofencing is a technique whereby an animal is trained to recognise and respond to a stimulus delivered to it via a GPS system when it steps out of a virtual arena which is only defined on a computer and not with a physical fence. It is especially relevant to very large extensive farms, or when the fence would otherwise need to be frequently moved. For example when stock are kept in a small area for intensive grazing, a virtual fence can be moved along the field each day. Geofencing has also been applied to large animals to alert rangers when they enter a village or agricultural area where they might cause harm (Licht *et al.* 2010, Hunter *et al.* 2007). The techniques described in this paper could make geofencing more practical, both by increasing its precision and by using behavioural as well as position data as an input.

Conclusions

GPS tracks can give valuable information about the movement and use of space of cattle (and other relatively large animals) and this can be visualized and analysed in software such as TrackLab. GPS tracking data can also be used to automatically detect a range of behaviours in cattle so long as these can be distinguished by the path of the animal in terms of the distance moved between samples (that is, its speed) and the turn angle between samples (that is, its meander). However, such analysis is limited when it comes to behaviours which have similar track patterns such as ruminating (lying down) and standing. Preliminary results with combining GPS and accelerometer data look very promising regarding the ability to be able to separate a wider variety of behaviours than with GPS data alone. This technique opens up a wide variety of possible applications for both farmers and agricultural researchers.

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