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Using accelerometer, high sample rate GPS and magnetometer data to develop a cattle movement and behaviour model

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ABSTRACT

The study described in this paper developed a model of animal movement, which explicitly recognised each individual as the central unit of measure. The model was developed by learning from a real dataset that measured and calculated, for individual cows in a herd, their linear and angular positions and directional and angular speeds. Two learning algorithms were implemented: a Hidden Markov model (HMM) and a long-term prediction algorithm. It is shown that a HMM can be used to describe the animal's movement and state transition behaviour within several "stay" areas where cows remained for long periods. Model parameters were estimated for hidden behaviour states such as relocating, foraging and bedding. For cows' movement between the "stay" areas a long-term prediction algorithm was implemented. By combining these two algorithms it was possible to develop a successful model, which achieved similar results to the animal behaviour data collected. This modelling methodology could easily be applied to interactions of other animal species.

1. Introduction

Grazing animals utilise a significant proportion of the global landscape, for example they occupy in excess of 50% of the Australian landscape ranging from improved pastures through to extensive rangeland environments (Gramshaw and Lloyd, 1993). Interactions between herbivores and their environments are spatially constrained and highly variable (Ash and Stafford Smith, 1996; Beecham and Farnsworth, 1999; Schwinning and Parsons, 1999; Van de Koppel et al., 2002). Wild herbivores are not constrained spatially unless they exist in parks that are fenced, where they are managed in ways similar to livestock. This paper focuses on livestock modelling since the GPS and magnetometer data were collected from farmed cattle that were contained by fences. Understanding sustainable grazing systems requires modelling methods that can accurately describe the individual components of herbivore behaviour (e.g. foraging, bedding, ruminating, relocating, etc.) as they interact across space and time. Accurate behavioural models provide important information about diet selection, herbage intake and how the grazing animal modifies the environment. Grassland ecosystems, which include herbivore behavioural interactions provide an ideal contextual scenario for applying innovative complex modelling procedures (Hastings and Palmer, 2003).

Previously, deterministic modelling of herbivore foraging has provided insights into the underlying processes that regulate plant animal interactions. However, methods that have used differential equations based on predator prey interaction models have the implicit and unrealistic assumption that foraging is evenly distributed in space and time (Noy-Meir, 1975). Spatial and temporal processes have been used to extend the deterministic approach and have included bite scale patches with variable foraging intervals (Parsons et al., 2001; Schwinning and Parsons, 1999). Although incorporating more realistic spatial and temporal models as the extension of deterministic models to include stochastic space and time within a stochastic mode of operation, it assumes animals defoliate bite sized patches randomly irrespective of patch state and relative location. The grazing animal's feeding choice is determined by its location in relation to the spatial arrangement of sward structural components (Grünbaum, 1998). Recent modelling has used spatially explicit methods to describe search rate and search distance, the results demonstrated the importance of spatial constraints in determining overall systems outcomes (Marion et al., 2005; Swain et al., 2007). Earlier authors have used Markov chain Monte Carlo methods within a Bayesian framework to estimate parameters for dynamic spatial models of animal behaviour using data from a field experiment exploring faecal avoidance in dairy cows (Marion et al., 2007) and a study of sheep feeding behaviour in an indoor arena (Walker et al., 2006).

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This paper explores a model of cattle movement. The modelling approach was compared to behavioural data collected from cattle and could be applied to interactions of other animal species. The modelling methods estimate behavioural parameter using high sample rate spatial monitoring of cattle movement.

Monitoring data (as well as empirical data derived from numerous hours of video and human observation) shows that cows like to stay in some areas for longer periods of time than other areas (Bailey, 1995, 2004). We refer to those regions where cows like to remain for prolonged periods (>1 h) as *stay* regions. Examples of stay regions could be boundary edges, shade and watering points. The remaining parts of the paddock were used to travel between stay regions and are referred to as travel regions. The cattle behaviour patterns vary between stay regions and travel regions. Animals stayed in different regions at different times of the day and each individual animal normally has its own behaviour pattern in each region. In the travel region, six cows followed almost the same trajectory. The travel regions were generally larger than the stay regions, so it is more efficient to use large scale modelling methods for travel regions. To develop a realistic model, two different modelling methodologies were implemented.

Hidden Markov models (HMMs) were used to predict individual cattle behaviour in each stay region. MacDonald and Raubenheimer (1995) modelled behaviour sequences using a HMM where the underlying unobserved behaviour was interpreted as motivational states; the current animal state (e.g. hungry) provided an indication of both the current behaviour (foraging) and associated behaviours (e.g. relocating, drinking, etc.). Franke et al. (2004) also used HMMs to analyse the behaviour of caribou, the probability transformation between the inferred behavioural states (bedding, foraging, relocating) was derived from observed state data (travel directional speed, travel direction, etc). The estimation procedure for HMM is based on expectation–maximization (EM) algorithm leading to an optimal state sequence.

It was also observed that animals travel directly from one stay region to another. Motion prediction can be used for objects that are able to perform trajectories as a result of an internal motion planning process or decision mechanism (e.g. persons, animals and robots). It is assumed that such plans are made with the intention to reach a specific goal, such as a water or shade area. In addition to the inferred behavioural states long-term trajectory prediction has been used to estimate future states using motion prediction (Vasquez et al., 2005). The animal trajectory and the association with inferred behavioural decisions was challenging, however, solving this problem has enabled more accurate animal behaviour models. Modelling methods that involved a two-stage process, model fitting and prediction, enabled an observed state model to be constructed and simulation estimates of future states derived based on the current knowledge (e.g. Osentoski et al., 2004). Vasquez et al. (2005) presented an on-line learning approach which was able to learn using HMMs; parameters were estimated incrementally as each observation became available using a Growing Neural Gas algorithm (Fritzke, 1995). A similar methodology was used in the current study, however, rather than using HMMs, animal movement was predicted using a clustering algorithm and Maximum Likelihood.

By combining HMMs and long-term trajectory prediction, a novel methodology is presented to model cattle's individual and herd behaviour on the basis of GPS and magnetometer data from a wearable collar. Based on such models, farmers and animal scientists can potentially select for desirable qualities that were previously hard to measure or not fully understood.

2. Methods

2.1. Data collection

The dataset used for the modelling came from six cows whose GPS position was recorded every 10 s for 4 days in July 2005. Each animal had a monitoring collar fitted which consisted of a Fleck^{TM} (Sikka et al., 2004) with wireless networking. The Fleck^{TM} was specifically designed for applications in animal tracking and control (Swain et al., 2007; Butler et al., 2006; Marsh, 1999; Tiedemann et al., 1999). The collar had a number of sensors including GPS, 3-axis accelerometer, 3-axis magnetometer and data storage capacity. The animals were able to move freely around a 7-ha paddock during data collection. The collar number, time (seconds), latitude and longitude were collected and saved in the dataset (Guo et al., 2006; Wark et al., 2007a). The dataset was used to learn about the properties of animal movement.

Longitude and latitude were converted to meters in the east and north directions which with time were used to show the animals' changing locations. Inter-animal distances were calculated from the positional data.

The 4-day dataset collected from the animals was split in half. The first half was used to develop the model and the second half for validation. The model training data-set was further divided and used to describe the activities within stay regions using HMMs and the movement between stay regions using long-term track prediction learning methodologies. The modelled animal movement data were implemented within a Matlab simulator to compare simulated results with the real data. Details of the model are as follows.

2.2. Model development

The model was developed using a combination of HMMs and long-term track prediction learning methodologies.

The model used a hierarchical structure (Fig. 1), including several sub-models:

1. The study area was separated into sub-areas of interest (stay regions and travel regions) according to GPS data as well as empirical data derived from numerous hours of video and human observation.
2. For each stay region, HMMs were generated for each cow using the corresponding observed data collected from its monitoring

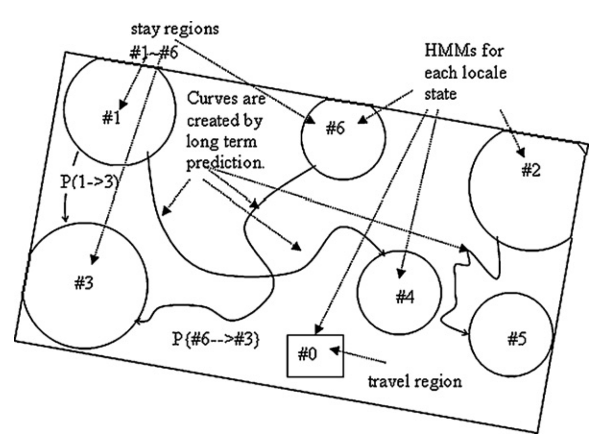

Fig. 1. The hierarchical structure of the animal model. Monitoring data (as well as empirical data derived from numerous hours of video and human observation) shows that cows like to stay in some areas for longer periods of time than other areas. We refer to those regions as stay regions (circles). The remaining parts of the paddock were used to travel between stay regions and are referred to as travel regions.