An Overview of Automatic Behaviour Classification for Animal-Borne Sensor Applications in South Africa

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ABSTRACT

Although South Africa has a rich wildlife heritage and a thriving domestic agricultural sector, thousands of animals are brutally poached or stolen every year. We describe a system capable of real-time automatic on-animal behaviour classification using animal-borne sensors. These classification decisions can be transmitted to a monitoring station to trigger appropriate and immediate response. We show how the system can be applied to the real-time monitoring of rhinoceros, thereby demonstrating its potential in nature conservation applications such as the fight against poaching. We also show the system's application to sheep to demonstrate its utility in the monitoring of livestock behaviour for precision farming applications.

CCS CONCEPTS

• **Hardware → Digital signal processing**; *Sensor applications and deployments*; Bio-embedded electronics;

KEYWORDS

Automatic Behaviour Classification; Accelerometer; GPS; Rhinoceros; Sheep

1 INTRODUCTION

South Africa is home to a wide variety of wildlife. This includes the iconic Big Five (African lion, African elephant, Cape buffalo, African leopard, and rhinoceros) which are admired both locally and internationally. However some of these animals have increasingly also become the victims of illegal poaching activity. Such poaching is sometimes motivated by superstitious beliefs that certain animal body parts have medicinal value. It may also be motivated by the social status bestowed by the possession of trophies, skins, tusks or horns. As animal populations decline, the body parts in question become rarer and their monetary value in illegal trading increases. This is especially true for rhinoceros horn [1] and has led to a dramatic population decline [2, 4, 5, 20] in areas such as the Kruger National Park (Figure 1). Figure 2 shows that, between 2007 and 2016, South Africa has lost more than 6100 rhinoceros due to poaching. This decline, as well as the brutal methods employed by the poachers, has afforded the fate of the African rhinoceros recent international attention.

Stock theft is also a problem in South Africa and has serious economic consequences for local farmers. Stock to the value of R4.6 billion was stolen over the last six years [3], with R819 million lost in the 2015/16 financial year alone [8]. Local farmers are desperately searching for new techniques to monitor their herds in order to be proactive in the fight against stock theft.

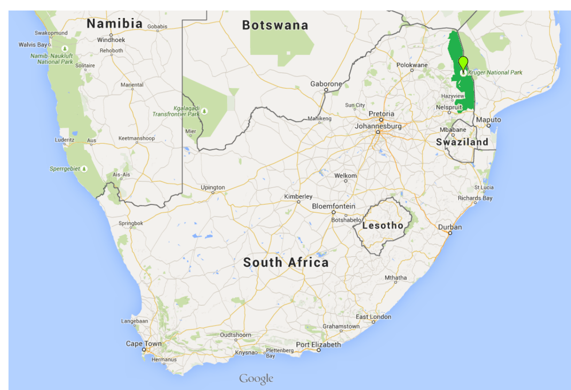

Figure 1: The Kruger National Park located in North West South Africa is home to the world's largest rhino population. Map data ©2017 AfriGIS (Pty) Ltd, Google.

The RhinoNet project at Stellenbosch University's Department of Electrical and Electronic Engineering is developing a technological platform aimed at assisting nature conservationists in their fight against rhino poaching. This paper provides a broad overview of the techniques being developed to allow real-time animal behaviour analysis. We also show how the same techniques can be applied to precision farming applications such as pasture management, and to gain insight into problems experienced by South African farmers such as stock theft and stock loss due to predation.

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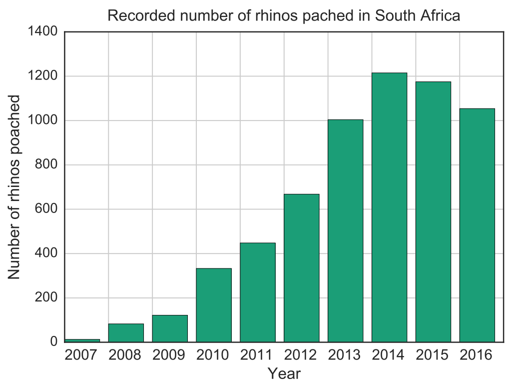

Figure 2: Recorded number of rhinos poached in South Africa from 2007 to 2016 [19].

2 AUTOMATIC ANIMAL BEHAVIOUR CLASSIFICATION

Recently several studies have used high resolution tri-axial accelerometer data to analyse the behaviour of various animals using statistical classifiers. Some of these are summarised in Table 1. The particular animal of interest typically needs to be collared with a biologging or biotelemetry tag which respectively log or transmit raw sensor data. Time-stamped video recordings of the animal's behaviour are often captured while raw data is collected. After a period of time the animal needs to be recaptured to retrieve the tag. The retrieved data is then used along with the video recordings to label the raw data according to a set of predefined behaviours. This labelled data set can subsequently be used to develop statistical classifiers and to evaluate their performance. Table 2 lists some common statistical classification techniques that have been applied to animal behaviour classification with high accuracies. To the best of our knowledge no study considered behaviour classification on the tag itself. Instead, current studies perform the classification as a post-processing step. This provides very valuable, but also historical information which is of great interest in fields such as biology and behavioural ecology. However, retrospective analysis of the data is not suitable for real-time nature conservation efforts. Therefore, we are developing a system which is able to produce behavioural updates in real-time while the sensor is attached to the animal.

3 ANIMAL-BORNE BEHAVIOUR CLASSIFICATION

In order to achieve real-time behavioural updates we are developing an embedded hardware implementation of conventional off-line automatic behaviour classification algorithms. To achieve this, a suitable optimised statistical classifier is implemented on the biotelemetry tag itself. Figure 3 shows the workflow of the animal-borne behaviour classification system. Sequences of tri-axial accelerometer measurements are acquired at a fixed sampling frequency. Features including acceleration maximum, minimum, mean and variance are calculated and presented as input to the on-board classifier which

Table 1: Animal and behaviour

Animal	Behaviour	Source
Baboon	Forage, Run, Rest, Stand, Walk	[6]
Badger	Walking, Trotting, Snuffling, Resting	[11, 12]
Cattle	Walking, Standing, Lying down, Ruminating, Feeding	[10, 16, 21, 22]
Cheetah	Feeding, Mobile, Stationary	[7]
Elephant	Feeding, Bathing, Walking, Swaying	[18]
Goat	Resting, Eating, Walking	[13]
Oystercatcher	Flying, Foraging, Handling prey, Sitting, Standing, Walking	[17]
Red Fox	Foraging, Leaps, Trotting	[15]
Vulture	Eating, Lying down, Active flight, Passive flight, Running, Standing, Preening	[14]

distinguishes between common behaviours. The classification result is then transmitted wirelessly to a receiver station for further analysis. The immediate availability of the behaviour information allows real-time analysis and decision making. Furthermore, transmission of the classification result as opposed to the acceleration measurements is advantageous from a power consumption point of view [9].

Table 2: Common statistical classification techniques that have been applied to animal behaviour classification.

Statistical classifier	Source
Artificial neural networks	[14]
Decision trees	[11, 12, 14, 16, 17, 21]
Discriminant function analysis	[18]
Hidden-Markov models	[7]
K-nearest neighbours	[11, 12, 15]
Linear discriminant analysis	[14]
Moving averages with thresholds	[13]
Quadratic discriminant analysis	[22]
Random forests	[6, 14]
Support vector machines	[7, 10, 14]

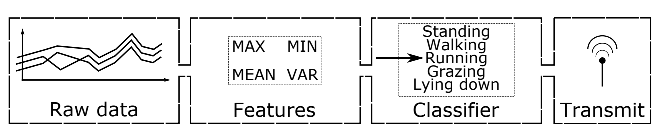

Figure 3: Workflow of the animal-borne behaviour classification system.

4 HARDWARE

Tags specifically optimised for low power consumption were developed for our application and a prototype is shown in Figure 4. The design uses a MSP430FR5739 low-power mixed signal microcontroller, a GNS602 GPS receiver, two FM25V20 ferro-electric non-volatile RAM (FRAM) storage modules (2 Mb each) and an ADXL345 tri-axial accelerometer. A low-power CC1101 sub-1 GHz RF transceiver allows wireless data communication at 433 MHz with an output power of 10 dBm and a bit-rate of 1.2 kBaud. Field tests indicate that a communication range of roughly 1 km can be expected with this configuration. However, the modular design allows the RF module to easily be replaced with higher power modules to adapt to an available terrestrial network, or a low power satellite transmitter can be added. Each printed circuit board (PCB) measures 100 mm x 60 mm x 12 mm and weighs 32 g. The tags are powered by a 3.7 V lithium-ion battery.

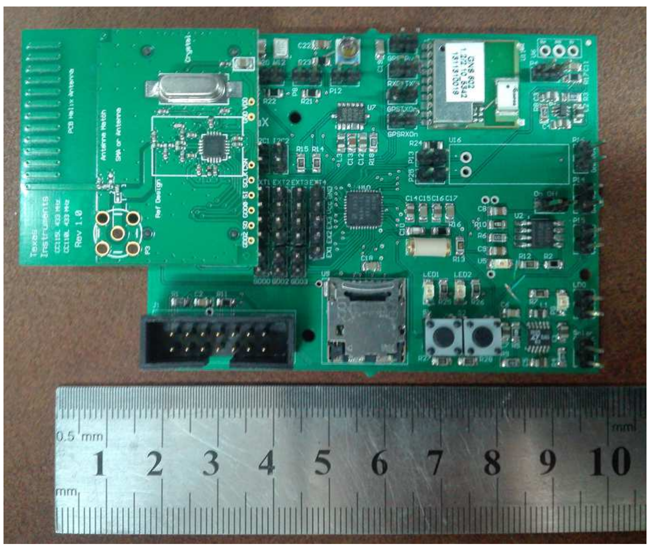

Figure 4: Hardware design of the biotelemetry tag. The tag's dimensions are 100 mm x 60 mm x 12 mm.

5 SYSTEM DEPLOYMENT ON SHEEP

Our system was deployed on sheep to investigate its utility in precision farming applications. The tags were enclosed in thick durable casings and attached to sheep as shown in Figure 5. The tags were configured to perform animal-borne behaviour classification, which produced and transmitted live behavioural updates every 5.3 s and achieved an accuracy of 82.4% among five behavioural classes: standing, walking, grazing, running and lying down.

Table 3 shows the average time spent in each of the five behavioural classes during four deployments. For each deployment five randomly selected sheep were tagged. The 1.5% of the time spent running accounts mainly for the daily collection of the sheep. We see that sheep spend most of their time lying down followed by walking and grazing. Very little time is spent standing still or running.

Figure 5: Biotelemetry tags attached to the necks of sheep.

This information can be used to develop an intuition or a statistical model for normal and abnormal sheep behaviour. For example, excessive running could indicate stock theft, a major problem for South African farmers. Similar considerations may be used to detect predator-livestock interactions, which also result in large stock losses and are particularly difficult to investigate by other means. Excessive lying behaviour, or disturbed walking and grazing behaviour, may on the other hand be an indicator of stock illness.

Live behavioural updates can also be used to perform extensive long-term habitat utilization studies, which are particularly useful in precision farming applications. Similar observations for wildlife are again useful in fields such as behavioural ecology. To date, such studies are primarily based on the analysis of GPS coordinates. For example, Figure 6 shows a heatmap calculated using 1000 GPS coordinates captured at 10 minute intervals of sheep movement within a 150 hectare camp. One can easily see where the animals spend most of their time. However, it is not clear what the animals were doing at the different locations. Animal-borne behaviour classification identifies both where the animal is and what the animal is doing. This can provide insight into the vegetation preference, where the animals tend to sleep or walk, and preferred home ranges.

Table 3: Total time (in hours) in each behaviour class by tagged sheep.

Period	Lying	Standing	Walking	Grazing	Running	Total
1	8.88	0.59	7.15	6.89	0.54	24.05
2	10.35	0.41	8.78	5.78	0.38	25.70
3	10.47	1.35	9.36	7.22	0.45	28.85
4	24.62	0.99	15.52	10.57	0.62	52.32
Total	54.32	3.34	40.81	30.46	1.99	130.92
%	41.5%	2.5%	31.2%	23.3%	1.5%	

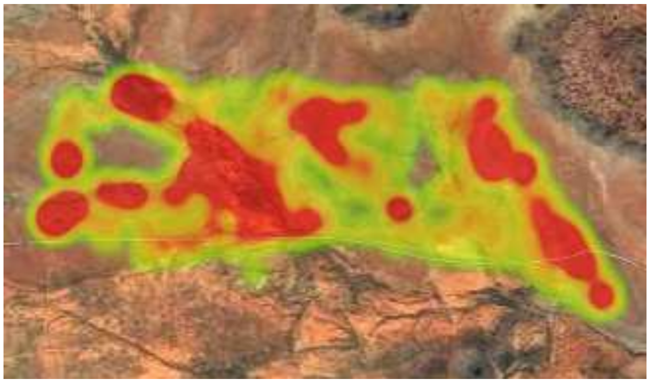

Figure 6: Heat-map of a sheep's movement within a 150 hectare camp.

6 SYSTEM DEPLOYMENT ON RHINOCEROS

Our system was also deployed on rhinoceros with the ultimate aim of assisting nature conservation and anti-poaching efforts. The tags were attached to the back leg of rhinoceros as shown in Figure 7. Using an on-board classifier trained and optimised for rhinoceros behaviour, the tags were configured to perform animal-borne behaviour classification, which produced and transmitted live behavioural updates every 6.5 s and achieved an accuracy of 96.1% among the three behavioural classes: standing, walking and lying down.

Table 4 shows the total time spent in each of the three behavioural classes by each rhinoceros over three deployments. During this time the animals were left undisturbed to roam freely over an area of roughly 100 hectares. We see that the rhinos spend most of their time standing and lying down, and least of their time walking. Figure 8 shows both the behaviour and movement patterns of the rhinos during the recorded period.

Figure 7: Biotelemetry tag attached to the left back leg of a rhino.

Table 4: Total time (in hours) in each behaviour class by tagged rhinoceros.

Rhino	Lying	Standing	Walking	Total
1	11.56	14.97	7.54	34.07
2	7.94	13.18	8.99	30.11
3	21.46	21.50	14.40	57.37
Total	40.96	49.65	30.93	121.55
%	33.8%	40.8%	25.4%	

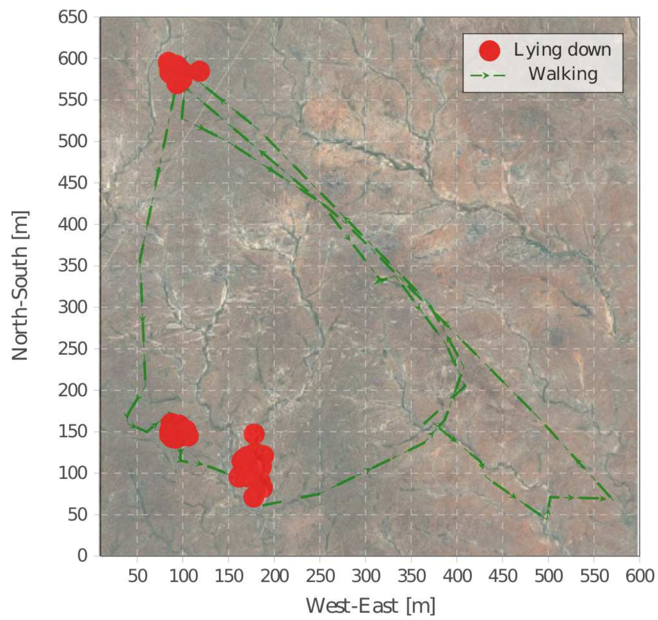

Figure 8: Locations at which the rhinoceros were lying down, as well as the routes taken when walking.

7 DISCUSSION AND CONCLUSION

Animal-borne behaviour classification provides real-time insight into animal behaviour that was previously only available much later during post-processing. It allows the remote collection of animal behaviour information which can be used to distinguish between normal and abnormal behaviour. This has the potential to assist in nature conservation efforts, such as the prevention of poaching, especially when the behavioural data is used to train machine learning algorithms. Although our system has so far been applied only to sheep and rhinoceros, it can in principle be extended to many other species. It also has broader applications in precision farming, such as smart livestock monitoring, and has the potential to support general biological behavioural research. Our continuing efforts are focussing on the further development and deployment for endangered wildlife species conservation.

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