Energy Benefits of On-Board Behaviour Classification for Animal-Borne Sensor Applications

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***Abstract*—The ability to study animal behaviour is important in many fields of science, including behavioural ecology, conservation and precision farming. These studies typically employ biotelemetry tags attached to animals to collect raw sensor data from tri-axial accelerometers. The lifespan of such tags is constrained by their power usage and is often a limiting factor when performing behavioural studies for extended periods of time. This study considers the effect on power requirements when performing statistical behaviour classification on the tag itself, as opposed to at a later stage, after raw data transmission. Such animal-borne classification is particularly attractive when live behavioural updates are required. Experiments using specially-designed low-power biotelemetry sensors demonstrated a 27-fold reduction in energy consumption when classification was performed on the tag, as opposed to conventional post-processing techniques. By performing on-board statistical behaviour classification, the power requirements are drastically reduced, thereby prolonging the lifespan of the tag.**

Keywords*—*Automatic animal behavioural classification, Accelerometer, Low power, Biotelemetry sensor.

I. Introduction

The study of animal behaviour has greatly advanced through the use of biotelemetry tags which include sensors such as Global Position System (GPS) trackers, tri-axial accelerometers, temperature sensors, pressure sensors and magnetometers [1]. These devices are typically attached to the animal of interest in order to periodically log or transmit raw sensor values. In the former case, the tag must be recovered to retrieve the data. The collected data is typically analysed using statistical or other computational techniques to achieve a common goal of many studies, namely the automatic classification of the animal's behaviour. Several studies have considered the determination of animal behaviour from acceleration measurements. For example, statistical classifiers have been shown to achieve good accuracies for badger [2], cattle [3–6], cheetah [7] and elephant [8].

Despite these advances, a major bottleneck in biotelemetry remains the fairly short lifespan of the tag due to the limited battery power. This can be a major constraint when applying automatic behaviour monitoring to real-world problems. Hence a reduction in the tag's power requirement has the direct and important benefit of extending its lifespan.

The authors would like to thank the National Research Foundation of the Republic of South Africa, Telkom South Africa, and Innovus of Stellenbosch University for funding the project.

In this work, we consider the effect on these power requirements of performing statistical classification on the tag itself, instead of at a remote location after raw data transmission or retrieval, as is currently done. This has recently been contemplated but not tested in a study concerning dairy cows [3]. We perform a set of detailed physical measurements of the energy consumption of a specially-designed low-power biotelemetry tag when configured to transmit raw acceleration measurements, and when configured to perform statistical behaviour classification and transmit the classification result. We will show that, although the computations required for classification are computationally expensive, this additional expenditure is more than compensated for by the more compact data which are subsequently transmitted, thus leading to a lower energy consumption and extended battery lifetime.

II. Methods

A. Animal-borne Behaviour Classification System

Animal-borne behaviour classification refers to the embedded hardware implementation of conventional off-line automatic behaviour classification algorithms. These algorithms are based on established machine learning techniques, which have recently been applied to the automatic behaviour classification of tri-axial accelerometer data for various taxa. Some common off-line techniques include decision trees [2,3,6], discriminant function analysis [8], hidden-Markov models [7], k-nearest neighbours [2], quadratic discriminant analysis [4] and support vector machines [5,7]. We consider the automatic classification of tri-axial accelerometer data into three behavioural classes using linear discriminant analysis (LDA). We extract the maximum, minimum, mean and variance for each of the three axes, resulting in 12 input features from frames of 256 sampled accelerometer measurements. Therefore, LDA involves a 12 by 3 matrix multiplication, which in our implementation requires 36 multiplications and 36 additions. In our case the classifier was implemented and field tested using biotelemetry tags attached to African rhinoceros (Ceratotherium simum and Diceros bicornis) [9], but this specific application is irrelevant to the analysis of energy consumption considered here.

B. Hardware

Our biotelemetry tags, shown in Fig. 1, are powered by a $3.7\,\mathrm{V}$ $(1800\,\mathrm{mAh})$ lithium-ion battery. The tags were optimized for low-power consumption and employ a low-power mixed signal microcontroller, a GPS receiver, two ferro-electric non-volatile RAM (FRAM) storage modules (2 Mb each) and a tri-axial accelerometer. A low-power sub-1 GHz RF transceiver allows wireless data communication at $433\,\mathrm{MHz}$ with an output power of $10\,\mathrm{dBm}$ and a bit-rate of $1.2\,\mathrm{kBaud}$. Field tests indicate that a communication range of roughly $1\,\mathrm{km}$ can be expected with this configuration. Each tag measures $100\,\mathrm{mm}$ x $60\,\mathrm{mm}$ x $12\,\mathrm{mm}$ and weighs $32\,\mathrm{g}$.

Table I lists the major power-consuming components used in the biotelemetry tags. Both the active mode and sleep mode current consumptions are shown.

TABLE I: Major power-consuming components of the biotelemetry tags, together with their active and sleep mode current consumptions.

Description	Part Number	Active Mode Current	Sleep Mode Current
Microcontroller	MSP430-FR5739	$1.628\,\mathrm{mA}$ @ $20\,\mathrm{MHz}$	$0.32\,\mathrm{uA}$
Tri-axial accelerometer	ADXL345	$170\,\mathrm{uA}$ @ $100\,\mathrm{Hz}$	$0.1\,\mathrm{uA}$
GPS	GNS602	$25\,\mathrm{mA}$ @ Acquisition	$7\,\mathrm{uA}$
FRAM non-volatile storage	FM25V20	$1.4\,\mathrm{mA}$ @ $40\,\mathrm{MHz}$	$3\,\mathrm{uA}$
Sub-1 GHz RF-transceiver	CC1101	$29.1\,\mathrm{mA}$ @ $433\,\mathrm{MHz}$ @ $10\,\mathrm{dBm}$	$0.2\,\mathrm{uA}$

C. Experimental setup

The hardware described in previous section was configured in two ways, as shown in Table II. Configuration 1 involves the transmission of the raw data, while Configuration 2 involves the transmission of the classification result. In each case, the power consumption was measured.

The biotelemetry tags were configured to sample the tri-axial accelerometer at a rate of $40\,\mathrm{Hz}$. Frames consisting of 256 sequential tri-axial samples were gathered. The raw samples were either transmitted, or were passed to the classifier, whose decision was transmitted. The current consumption was measured as a function of time so that the energy requirements of each activity could be accurately identified and quantified.

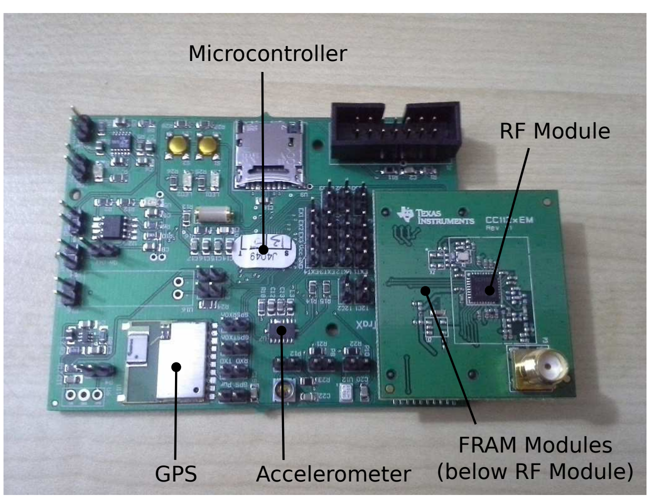

Fig. 1: Assembled biotelemetry tag. The tag measures $100\,\mathrm{mm}$ x $60\,\mathrm{mm}$ x $12\,\mathrm{mm}$ and weighs $32\,\mathrm{g}$.

TABLE II: Two hardware configurations used in power measurements.

Configuration	Description
1	Sample and transmit raw accelerometer data.
2	Sample accelerometer data, classify behaviour and transmit the classification result.

III. Results

A. Configuration 1: Sample and transmit raw accelerometer data.

At a sample rate of $40\,\mathrm{Hz}$, the 256 tri-axial accelerometer measurements are captured in $6.4\,\mathrm{s}$. When the values are written to the FRAM, the current consumption is constant at $1.69\,\mathrm{mA}$, shown in Fig. 2. After sampling and storing the 256 tri-axial accelerometer measurements, the data is transmitted to a receiver station for further processing. Fig. 2 shows that, in addition to the $6.4\,\mathrm{s}$ required to sample and store the raw data, a further $10.43\,\mathrm{s}$ is required to transmit the raw information. During transmission the current consumption is $32.56\,\mathrm{mA}$.

B. Configuration 2: Sample accelerometer data, classify behaviour and transmit the classification result.

As before, 256 tri-axial accelerometer measurements are sampled and temporarily stored. This sequence of acceleration measurements is then processed by the on-board classifier to yield the classification result. The classification result is encoded as a single byte whose value indicates the classified behaviour. Fig. 3 shows that, after the $6.4\,\mathrm{s}$ needed to acquire the raw data, the microcontroller spends $73.76\,\mathrm{ms}$ classifying and storing the result, while consuming $2.08\,\mathrm{mA}$. The classification result is subsequently transmitted, requiring a further $55.4\,\mathrm{ms}$. As before, the current consumption during transmission is $32.56\,\mathrm{mA}$. Behavioural updates are therefore available every $6.53\,\mathrm{s}$.

IV. Discussion

Table III summarises the measurements obtained from the two experimental configurations. The table indicates the average current consumption per frame, Joules of energy required,

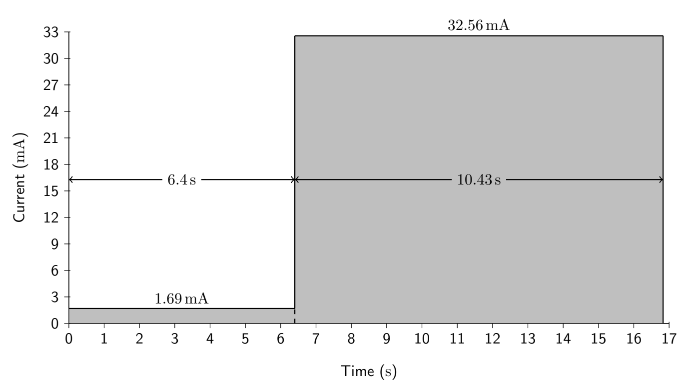

Fig. 2: Current consumption as a function of time for Configuration 1 (sample and transmit raw data).

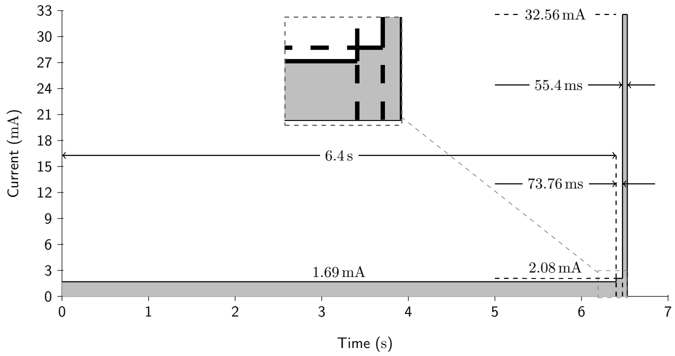

Fig. 3: Current consumption as a function of time for Configuration 2 (sample, classify and transmit decision).

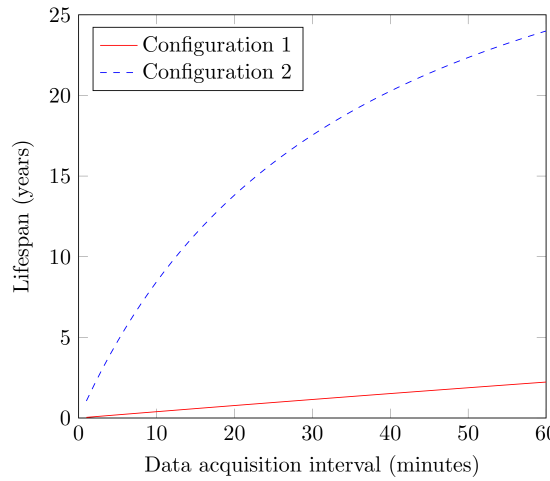

Fig. 4: Theoretical lifespan of the tags for various data acquisition intervals. Calculations are based on a $3.7\,\mathrm{V}$ $(1800\,\mathrm{mAh})$ lithium-ion battery.

and the time required to process one frame of 256 successive acceleration measurements.

Analysing Table III shows that behavioural updates can be obtained while consuming 27 times less power per frame when on-animal classification is performed.

TABLE III: Summary of results.

Configuration	**Average current consumption** (mA)	**Joules per frame**	**Period per frame (s)**
1	20.821	1.156378	16.83
2	1.956	0.042150	6.53

A. Reduced update frequency

Although Configurations 1 and 2 can produce raw or classified updates every $16.83\,\mathrm{s}$ or $6.53\,\mathrm{s}$ respectively, behavioural updates are in practice typically required less frequently. In this case, biotelemetry tags enter into a low-power sleep mode (in our case consuming $6.065\,\mathrm{uA}$) between updates. This further increases the lifespan of the tags. Fig. 4 contrasts the extrapolated lifespan of Configurations 1 and 2 for the same range of data acquisition intervals. Note that spontaneous deterioration of the battery due to, for example, internal discharge has not been taken into account. Analysing Fig. 4 shows that, when live behavioural update are transmitted every 5 minutes, the tags have an expected battery life of 4.75 years. This is in contrast with a lifespan of 71 days when raw data is transmitted.

V. Summary and Conclusion

We have considered the implications on power requirements of performing statistical classification of tri-axial accelerometer measurements into behavioural classes directly on biotelemetry tags as opposed to at a receiver station after wireless data transmission. A LDA-based statistical classifier implemented on a low-power biotelemetry tag achieved a 27-fold reduction in power consumption when compared with a system in which the raw acceleration data was transmitted. We conclude that animal-borne behaviour classification is advantageous from a power consumption standpoint. This applies especially to applications where the transmission of data can not be avoided because, for example, real-time updates are essential. The power savings afforded by on-animal classification can enable long-term real-time behavioural studies. It may also assist in real-world applications such as nature conservation, precision farming as well as veterinary and epidemiological research.

References

[1] R. Kays, M. C. Crofoot, W. Jetz, and M. Wikelski, “Terrestrial animal tracking as an eye on life and planet,” *Science*, vol. 348, no. 6240, 2015.

[2] D. W. McClune, N. J. Marks, R. P. Wilson, J. D. Houghton, I. W. Montgomery, N. E. McGowan, E. Gormley, and M. Scantlebury, “Tri-axial accelerometers quantify behaviour in the Eurasian badger (Meles meles): towards an automated interpretation of field data,” *Animal Biotelemetry*, vol. 2, no. 1, p. 5, 2014.

[3] J. A. Vázquez Diosdado, Z. E. Barker, H. R. Hodges, J. R. Amory, D. P. Croft, N. J. Bell, and E. A. Codling, “Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system,” *Animal Biotelemetry*, vol. 3, no. 1, p. 15, 2015.

[4] N. Watanabe, S. Sakanoue, K. Kawamura, and T. Kozakai, “Development of an automatic classification system for eating, ruminating and resting behaviour of cattle using an accelerometer,” *Grassland Science*, vol. 54, no. 4, pp. 231–237, 2008.

[5] P. Martiskainen, M. Järvinen, J.-P. Skön, J. Tiirikainen, M. Kolehmainen, and J. Mononen, “Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines,” *Applied Animal Behaviour Science*, vol. 119, no. 1, pp. 32–38, 2009.

[6] B. Robert, B. White, D. Renter, and R. Larson, “Evaluation of three-dimensional accelerometers to monitor and classify behaviour patterns in cattle,” *Computers and Electronics in Agriculture*, vol. 67, no. 1, pp. 80–84, 2009.

[7] S. Grünewälder, F. Broekhuis, D. W. Macdonald, A. M. Wilson, J. W. McNutt, J. Shawe-Taylor, and S. Hailes, “Movement activity based classification of animal behaviour with an application to data from cheetah (Acinonyx jubatus),” *PLoS One*, vol. 7, no. 11, p. e49120, 2012.

[8] J. Soltis, R. P. Wilson, I. Douglas-Hamilton, F. Vollrath, L. E. King, and A. Savage, “Accelerometers in collars identify behavioural states in captive african elephants Loxodonta africana,” *Endangered Species Research*, vol. 18, no. 3, pp. 255–263, 2012.

[9] S. P. le Roux, R. Wolhuter, and T. Niesler, “An overview of automatic behaviour classification for animal-borne sensor applications in south africa,” in *SAWACMMM’17*, October 23, 2017, Mountain View, CA, USA.