Assessing Physical Activity of Farm Animals with a Proxy Measure from Wearable Devices

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Abstract— **Through an understanding of animal activities, one is able to better infer large scale ecological and epidemiological processes. Recent advances in wildlife monitoring offer the opportunity to reduce the time and monetary costs of traditional animal surveillance, but most importantly, such advances offer greater overall geospatial accuracy than traditional camera traps or surveys. However, no systems have been identified that provide nuanced details of behavior such as walking, resting, or playing without the use of GPS. This paper presents pilot work to develop a system designed to identify physical activities of large animals.**

I. Introduction

Social behavior in beef cattle is complex and few fine-scale investigations have been conducted. In an effort to better understand the transmission of disease in domestic animal networks, Chen et al [1] observed the spatial-temporal dynamics of cattle over seven days. Their findings show that the majority of contacts occur during feeding time. However, in this study, the cattle were constrained to a $200m^2$ pen.

Direct observation of cattle and recording all social interactions and physical activity changes is impractical, especially when they free-range over a large geographic space. However, it is now possible to instrument cattle and other large animals with the appropriate tool set to measure and record activity and movement [2]. The technology of animal tracking collars has not seen any great advancements in the past few years and most researchers rely on time stamped Global Positioning System (GPS) coordinates. However, GPS inaccuracies prevent fine-scale measurements needed to classify and quantify activities and social interactions.

II. Methods

To start, we designed and fabricated an accelerometer enabled cattle collar. The cow was filmed while wearing the collar. An external light emitting diode binary clock was used to synchronize the video and accelerometer data sets. Video based analysis was used to identify during what times the cow was standing, walking, running, or fidgeting. We collected 20 minutes of data, with measures of time of day, time since start of data collection (recorded in milliseconds), and the three axes of linear accelerations. The collar logged over 160 thousand samples, or nearly a half million data points.

After the video and accelerometer data was time registered, the video determined activity classifications, with the associated start and stop times, were used to sub-select the raw data for use in a each of the statistical learning classifiers.

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	19967 **Stand**	8056 **Fidget**	21832 **Walk**	1170 **Run**
pred(**Stand**)	**58.88%**	57.27%	50.59%	56.24%
pred(**Fidget**)	0.56%	**0.24%**	0.45%	0.00%
pred(**Walk**)	40.56%	42.49%	**48.96%**	43.76%
pred(**Run**)	0.00%	0.00%	0.00%	**0.00%**

TABLE I: This table shows the number instances of each condition (stand, fidget, walk, and run in the first row) as well as the percentage of each that was categorized as stand, fidget, walk, and run as found using the multinomial logistic regression classifier (in each column).

	19967 **Stand**	8056 **Fidget**	21832 **Walk**	1170 **Run**
pred(**Stand**)	**16.16%**	6.01%	11.35%	2.91%
pred(**Fidget**)	38.65%	**69.10%**	45.16%	11.62%
pred(**Walk**)	4.42%	5.71%	**8.61%**	2.22%
pred(**Run**)	40.77%	19.18%	34.88%	**83.25%**

TABLE II: This table mirrors Table I, but instead reflects the results of the linear discriminant analysis classifier.

III. Results

The results of each classifier are shown in Tables I and II. As is seen here, multinomial logistic regression proves to be unable to reliably identify any activity without a significant degree of misclassification from other categories. The linear discriminant analysis classifier was only marginally better; it was able to catch most all cases of running, but at the cost of misclassifying many of the other categories as well.

IV. Discussion and Conclusions

The results of each classifier show drastically different bias, suggesting that use of raw acceleration alone is insufficient to accurately identify physical activities of cattle. Yet at the same time, these results show promise for developing the methods of assessing physical activity through a proxy device such as a wearable accelerometer. Further studies are needed to establish an appropriate taxonomy for cattle movements and the ability to reliably identify such movements.

References

[1] Shi Chen, Amiyaal Ilany, Brad J White, Michael W Sanderson, and Cristina Lanzas. Spatial-Temporal Dynamics of High-Resolution Animal Social Networks: What Can We Learn from Domestic Animals? Shi Chen, Amiyaal Ilany, Brad J. White, Michael W. Sanderson, and Cristina Lanzas.

[2] Christopher C. Wilmers, Barry Nickel, Caleb M. Bryce, Justine A. Smith, Rachel E. Wheat, Veronica Yovovich, and M. Hebblewhite. The golden age of bio-logging: How animal-borne sensors are advancing the frontiers of ecology. *Ecology*, 96(7):1741–1753, 2015.