IoT at the Grassroots – Exploring the Use of Sensors for Livestock Monitoring

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IoT at the Grassroots – Exploring the Use of Sensors for Livestock Monitoring

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Abstract: In this work we explore the use of cheap sensors to monitor the activities of dairy cattle with the aim of using these sensors as part of a system to detect important events such as when a cow is ill or on heat. This draws on advances in human activity recognition (HAR) where wearable sensors are used to collect data and infer human activity. Our sensor system is based on the Raspberry Pi microprocessor interfaced to an accelerometer sensor. We explore the use of simple machine learning techniques to infer activity from the data we collect and show that our simple system has the potential to detect different animal activities such as walking, standing and feeding. We also test the system on detection of human activities collected under controlled conditions to demonstate the potential use of the system. We envision an internet of things (IoT) system with cows in a herd mounted with appropriate sensors which relay information to servers over the internet. Farmers are then able to access information about their cattle at any time and take appropriate action when events of interest are detected.

Keywords: Internet of things, activity detection, Raspberry Pi, machine learning

1. Introduction

Agriculture is the mainstay of several African economies and there is need to improve productivity in both livestock and food production to meet the growing food needs due to population increase. To achieve this, we must take advantage of modern technology and investigate the most appropriate ways to deploy these technologies. In particular, recent advances in sensor technology and methodologies for extracting useful information from data collected from these sensors can play an important role in securing Africa's food future.

Two major technological advances have dominated the last decade. One is the Internet of Things (IoT) and the other is the processing of "Big Data". The Internet of Things refers to systems of interconnected devices all able to communicate to one another over the internet designed to achieve a specific goal [1]. These systems include sensor networks that can be of use in agriculture such as systems to monitor greenhouses and dairy cattle enclosures. Big data on the other hand is a term that has been coined to refer to the large amounts of data that are now being generated by these interconnected devices. These data are generated in high volumes and at high velocity. For example, sensors may take measurements several times a second. IoT and Big data can be used to improve livestock productivity in Africa and one sector in need of these technological interventions is dairy farming.

In Africa, dairy farming plays a fundamental role in the lives of a large segment of the population. Whether one is a smallholder with a single cow or a large scale farmer with dozens of animals, the challenge of achieving high milk yields while keeping the costs of production low remains the same. Modern technology and in particular techniques for monitoring the wellbeing of animals in real time can be used to enable the achievement of high productivity in the face of limited and possibly diminishing resources such as pasture and clean water. While the need for a study to identify which technological interventions would yield the most return on investment in dairy farming is clear, few studies have been undertaken to achieve this goal.

Efforts to harness the power of technology for livestock monitoring have been applied successfully in a number of countries. The system described in [2] proposes development of a 'smart farm' where all aspects of the farm from animal well being to the condition of pasture are monitored continuously using a wide range of wireless nodes equipped with sensors. In [3, 4] the authors propose use of radio frequency identification (RFID) technology to monitor dairy herds in order to improve productivity. In these studies, technological interventions are being applied to reasonably modern dairy farms equipped with modern dairy equipment such as milking machines. In the African setting, few farms are equipped with milking machines. However, work in India [5] has shown that even in developing nations, RFID technology can help small scale rural farmers.

In this paper we seek to demonstrate how cheap accelerometer sensors can be used to monitor the activity of dairy cattle. This information can then be used to determine important events such as when the cow is sick or on heat. The work we present draws on progress made in the recent past in the area of human activity recognition (HAR) [6,7]. HAR is important in monitoring the health of individuals since activity is associated to health. A number of lifestyle diseases are associated with inactivity and accurate methods of measuring a person's activity level can be used to determine their predisposition to certain diseases [8]. We aim to leverage these developments and apply them to the monitoring of livestock. In particular we aim to focus on monitoring dairy cattle for any signs of illness or to determine when the cows are on heat (estrus).

Estrus detection is important in dairy cow management because missed detections lead to low calving rates in the herd which in turn results in low milk production [9]. However heat detection is a difficult problem and several farmers identify this as a key challenge in dairy farming. If heat is detected late, it can lead to procuring artificial insemination (AI) services at an inappropriate time which reduces the success rate of AI. Since AI services are not cheap, any unsuccessful AI is expensive to the farmer and reduces profitability. This has motivated our work which aims to leverage modern technology to develop a simple device capable of effectively detecting heat in cows and also detecting other states such as illness. This device is based in the hypothesis that these states influence the cow's activity levels and also have certain associated activities. For example, cows on heat stand to be mounted by other cows, mount other cows, exhibit restlessness and eat less than other cows [10]. In addition, a sick cow may exhibit inactivity and low food intake. These states can be inferred using data collected by a simple accelerometer. Here, we show a prototype device and sample data collected by the device. We also demonstrate how activity can be inferred from the data collected using machine learning methods. We also propose that such a system can be deployed to a dairy farm as an IoT system with all cows in the herd mounted with a sensor capable of communication to a cloud server over the internet.

2. Objectives

The main objectives of this work are:

1. To develop a prototype sensor system capable of obtaining accelerometer data from dairy cattle
2. To develop methodology for activity detection for dairy cattle using accelerometer data
3. To relate activity patterns to important events such as estrus (heat) and illness

3. Methodology

A number of systems have been developed which use accelerometer sensors for human activity recognition [6,7]. An accelerometer measures acceleration in three perpendicular directions and this can be used to estimate the acceleration of a body to which the sensor is attached.

Using the accelerometer we can obtain time series of acceleration in the three axes for different activities and based on these patterns we can classify the activities being performed. To determine the activity automatically, we must derive relevant features from the time series. With these features we will then train classifiers to automatically recognize actions. The first step involves division of the time series into blocks, here we use non-overlapping blocks of 64 samples each. This corresponds to blocks 1.28 seconds long at 50Hz. For each block we compute the following features [6]:

1. The mean of the samples
2. The standard deviation of the samples
3. The difference between the maximum sample and the minimum sample as a measure of the peak to peak difference
4. The signal power, the sum of the squares of the sample values
5. The one lag correlation of the signal. This value is high when the signal exhibits a periodic pattern
6. The crosscorrelation between different axes

For the three axes we obtain a feature vector of length 18.

Using these features obtained from training data, we trained a K nearest neighbour classifier to determine the activity associated with test segments. This was done for both human activities and cow activities. The K nearest neighbour classifier works by determining the K closest training segments to the test segment and assigning the test segment to the class of the majority of these K training segments [11]. We programmed our system in python using the K nearest neighbor implementation provided in the Scikit-learn package (http://scikit-learn.org/).

4. Technology Description

In this work we demonstrate the collection of accelerometer data from dairy cows with the aim of determining the cow's activity and inferring states of interest such as illness and heat. The system we propose will leverage developments in IoT which provides a framework to allow several interconnected devices to collect data of interest in a given problem. However, currently only the sensor nodes have been developed and communication to the internet via a gateway has yet to be implemented. Therefore once the data are collected, they must be manually retrieved.

Here we explore the development of the sensor nodes that will form part of the IoT system. Our sensor nodes use the Raspberry Pi (RPi) microprocessor to collect data from the ADXL345 accelerometer from Analog devices (www.analog.com/en/products/mems/accelerometers/adxl345.html). The ADXL345 is a low power, 3-axis accelerometer capable of measuring acceleration up to +/-16g ($g=9.81m/s^2$). It is connected to the RPi via the general purpose input and output (GPIO) pins with the system powered via a 3.7 V Lithium polymer (Lipoly) rechargeable battery. Since the RPi requires approximately 5V to operate, we use the powerboost system from Adafruit to bring the voltage to the required 5V. Communication to the sensor is controlled by a python script which allows us to set the sampling rate and recording duration. The RPi is programmed to begin data collection at boot time and data collection is at one minute intervals for approximately 30 seconds at a sampling rate of 50Hz. Figure 1A shows the prototype system. Figure 1B shows the system attached to a dairy cow's neck using a strap with the orientation of the various axes indicated.

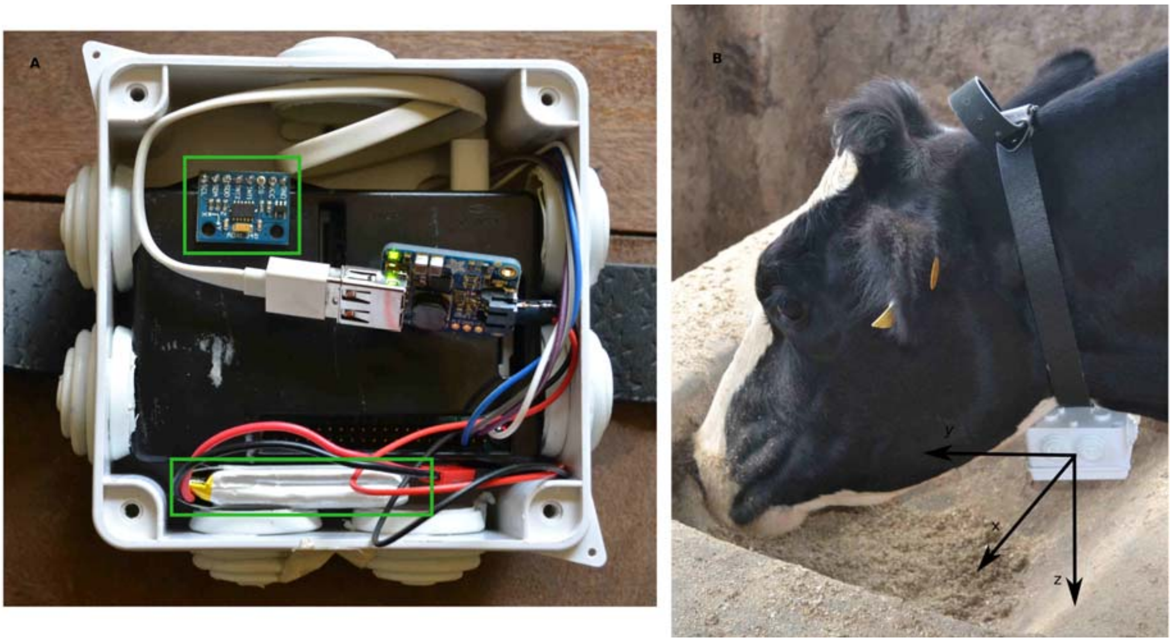

Figure 1: The prototype sensor system (A). The green square at the top shows the ADXL345 accelerometer sensor while the square at the bottom indicates the Lipoly battery. The system attached to a dairy cow's neck using a strap (B). The orientation of the various axes is indicated.

5. Results

To determine the efficacy of the proposed system, we performed preliminary experiments with the aim of classifying both human and dairy cattle actions based on accelerometer data. These data were collected by the author as the human subject and on a dairy cow observed by the author for approximately 30 minutes. In total 12 recordings of human actions and 37 recording of cow actions were obtained each 30 seconds long. 9 recordings of cow actions contained multiple actions and could not be assigned to a single activity class and therefore only 28 recordings of cow actions were used in the experiments. Each of the recordings was labelled with its corresponding action. Table 1 shows a summary of the data collected.

Figure 2 shows accelerometer patterns obtained for four human activities namely sitting (A), walking (B), climbing up stairs (C) and climbing down stairs (D). These time series were obtained using our prototype device described in section 4 by attaching the device using a strap to the waist of the author. The data are sampled at 50Hz. From the time series, we see that the different activities produce different patterns. Figure 3 shows the time series obtained when the prototype device was attached to the neck of a dairy cow by means of a strap as shown in Figure 2B. The cow was observed for approximately 30 minutes and its activities noted. Time series corresponding to different activities are shown in Figure 3 and these are eating at a trough (A), eating grass in a paddock (B), standing (C) and walking (D).

Subject	Activity	Number of Files
Human	Sitting (HS)	3
	Walking (HW)	3
	Climbing up stairs (HUS)	3
	Climbing down stairs (HDS)	3
Cow	Eating at a trough (CE1)	5
	Eating grass (CE2)	7
	Standing (CS)	6
	Walking (CW)	10
	Mixed actions (CMA)	9

Table 1: Summary of data collected. Short codes for the activities are indicated

To train the K nearest neighbour classifier, the features described in section 3 were derived from blocks of 64 samples (1.28 seconds at 50Hz). The data were randomly divided into two with 70% of the data used for training and 30% used for testing. For various values of K we determine the performance of the classifier by computing the precision and recall. Precision and recall are defined as follows:

$$Precision=\frac{TP}{TP+FP}$$

$$Recall=\frac{TP}{TP+FN}$$

Where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives. For an ideal classifier precision and recall are both 1. The experiment was repeated 100 times to obtain the average precision and recall for each activity for various values of K. The results are shown in Table 2 (We use the short codes for the activities introduced in Table 1). Code and data to reproduce these experiments is available on github (https://github.com/ciiram/CowActivityDetect).

From these results we see that the classification of human actions is successful even with a simple nearest neighbour classifier. On the other hand the classification of cow actions using this simple method is less successful. This could be due to the signals containing several actions over a short duration. For example, the cow could be walking with short pauses in between. Also, as the cow eats, it may pause to chew. This means that more sophisticated machine learning methods may be necessary for these complex actions. However, this preliminary work shows that the classification of actions based on accelerometer data is possible.

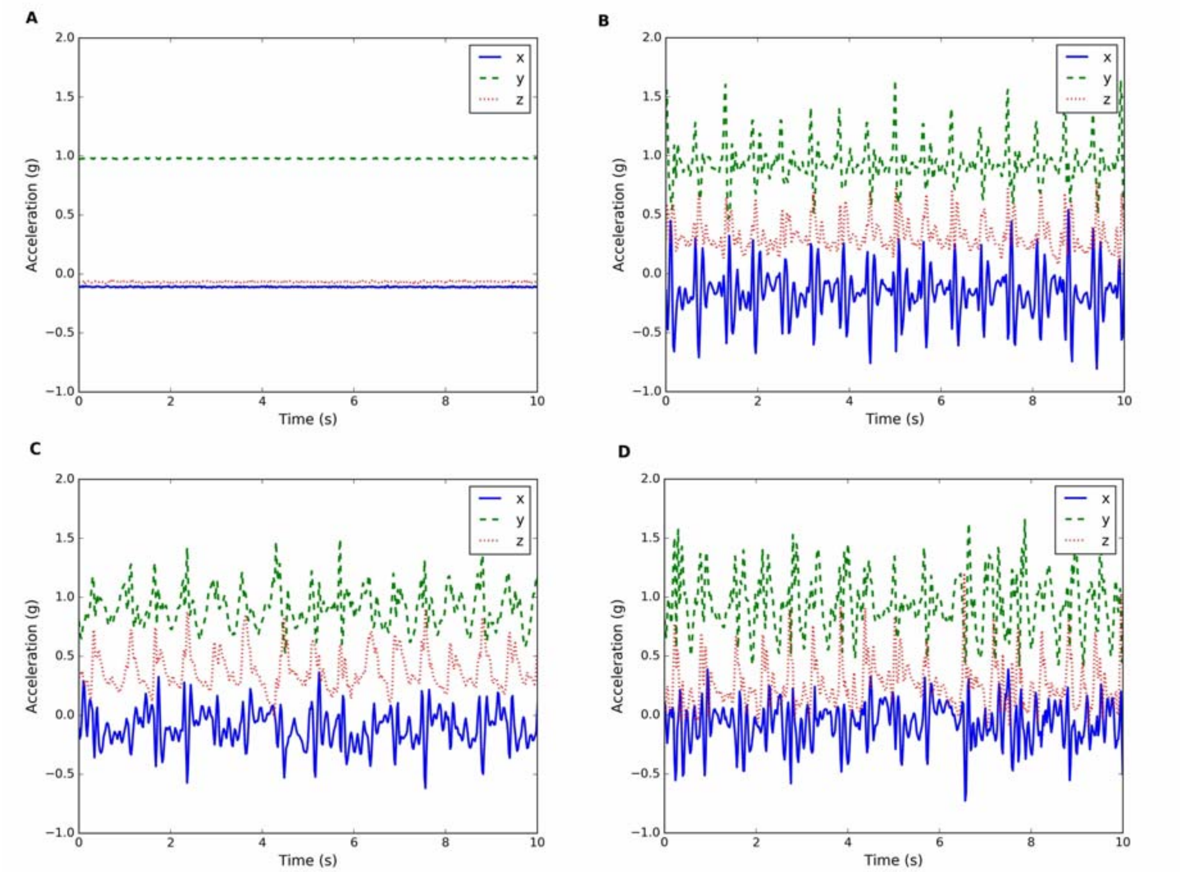

Figure 2: Accelerometer patterns obtained for four human activities namely sitting (A), walking (B), climbing up stairs (C) and climbing down stairs (D).

Activity	K							
	1		3		5		10	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
HS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HW	0.90	0.98	0.86	0.97	0.85	0.97	0.82	0.97
HUS	0.97	0.92	0.98	0.91	0.98	0.90	0.97	0.90
HDS	0.94	0.92	0.95	0.89	0.95	0.89	0.96	0.84
CE1	0.42	0.39	0.39	0.55	0.39	0.43	0.40	0.41
CE2	0.65	0.65	0.66	0.66	0.64	0.69	0.63	0.71
CS	0.52	0.59	0.63	0.55	0.54	0.55	0.53	0.54
CW	0.58	0.55	0.62	0.53	0.61	0.52	0.60	0.53

Table 2: K nearest neighbour classifier performance for various activities as a function of K.

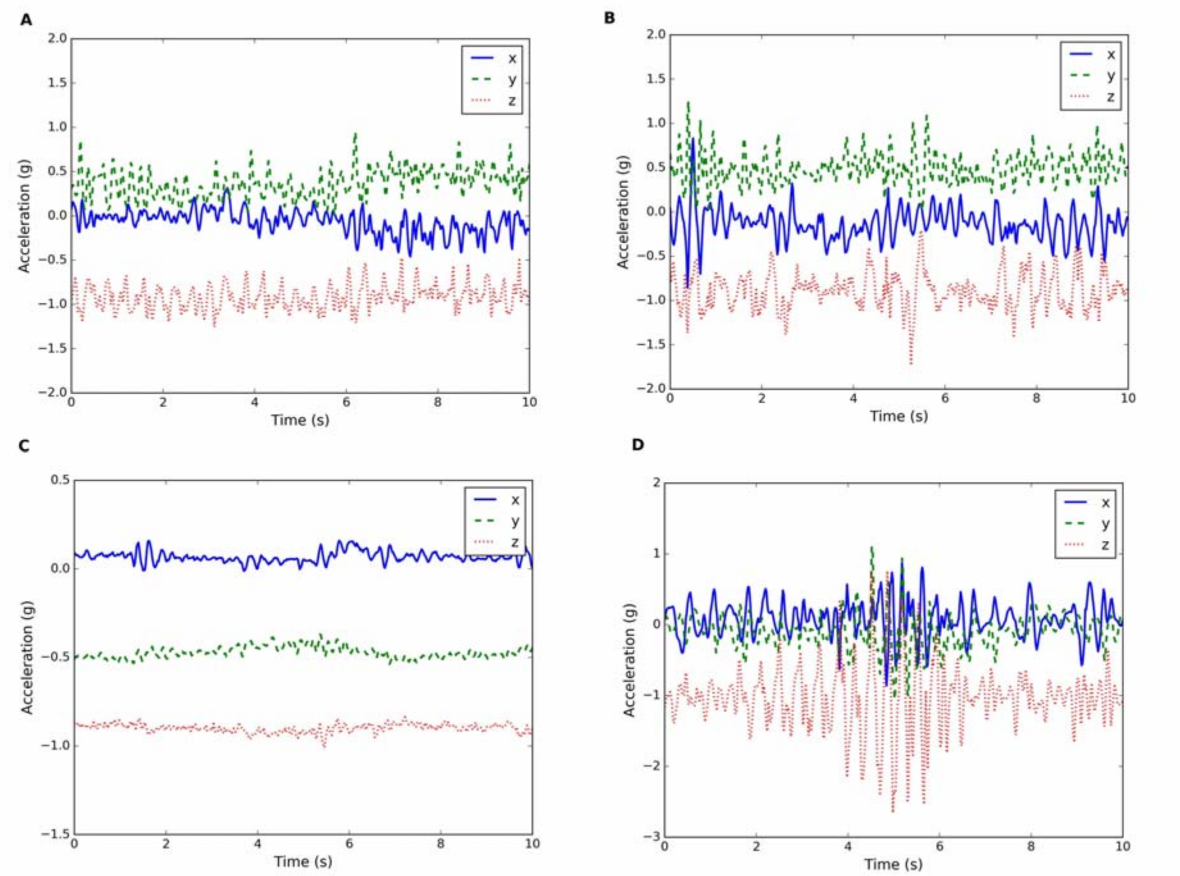

Figure 3: Time series corresponding to different cow activities. These are eating at a trough (A), eating grass in a paddock (B), standing (C) and walking (D).

6. Business Benefits

Dairy farming is an important economic activity and technological interventions to improve productivity can have a huge impact. Illness in the herd can result in huge losses due to reduced production and death of livestock. Also, in dairy cow management it is important to ensure most of the cows are in calf so that milk production remains high. For this to happen, a farmer must detect when a cow is on heat and ensure it is served with quality semen during artificial insemination (AI). Heat detection requires careful observation of the herd and adequate expertise and when this is unavailable it results in cases of missed detections which results in low calving rates in the herd. As a result, milk production is reduced leading to losses. The system we propose has the potential to reduce these losses.

In Kenya a good dairy cow can cost as much as $2,000 and most dairy cows owned by small holders cost approximately $500. This represents a considerable investment and our system could help reduce the risk of loss. Also, procuring AI services costs between $15 and $100 per service depending on the quality of the semen. If heat is detected late, this reduces the chance of fertilization and this means that service must be repeated at additional cost .

7. Conclusions

Here we propose a cheap prototype sensor that can be used to detect the activity of a cow. These data can in principle be used to infer when a cow is ill or on heat. The device forms part of the IoT system we envision where with all cows in the herd mounted with the sensor we can detect behavior which indicates illness or signs of heat. We propose to have these sensors relay their measurements to a cloud server over the internet and these data can then be processed and information relayed to the farmer about the status of each of the animals in the herd.

Our initial experiments showed that it was possible to detect both cow and human activities using accelerometer data collected using our prototype system. For cow data collected on a farm, the performance was reduced due to the fact that cows rarely perform actions in isolation and this requires exploration of appropriate machine learning algorithms capable of handling this complexity. Future work aims to integrate this sensor system into a complete IoT system capable of detecting cow activity in real time and inferring important states such as heat and illness.

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