Animal Behaviour Understanding using Wireless Sensor Networks

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Abstract

This paper presents research that is being conducted by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) with the aim of investigating the use of wireless sensor networks for automated livestock monitoring and control. It is difficult to achieve practical and reliable cattle monitoring with current conventional technologies due to challenges such as large grazing areas of cattle, long time periods of data sampling, and constantly varying physical environments. Wireless sensor networks bring a new level of possibilities into this area with the potential for greatly increased spatial and temporal resolution of measurement data. CSIRO has created a wireless sensor platform for animal behaviour monitoring where we are able to observe and collect information of animals without significantly interfering with them. Based on such monitoring information, we can identify each animal's behaviour and activities successfully.

1. Introduction

Pasture-based livestock production accounts for 72% of the value of the total livestock production in Australia, but is exposed to global trends including climate change, the ageing workforce, the rising cost of fuel and increasing environmental regulation affecting "permission to farm". These have the potential to increase the cost of livestock production considerably, and even make many current systems unviable.

This paper presents the research that is being conducted by the CSIRO[1] with the aim of investigating the use of wireless sensor networks for automated animal monitoring and control. Potential applications for control are the need to keep livestock in certain areas or the ability to herd livestock moving along a path. In order to achieve this however, the very fundamental question needs to be answered as to whether livestock is in fact controllable. Previous experiments by Vaughan et.al. [1] show that a duck can be controlled by an external agent such as a robot. Tiedemann et. al. [2] shows that cows are at least partly controllable by using the combination of audio warning signals and electrical stimulus on the animal ears.

The work in [2] also shows it is not an easy task to control cows. One reason is that people do not fully understand livestock's normal behaviour and the way in which different livestock can respond quite differently to the same input stimuli. As a result there is currently no "good model" to describe this varying behaviour.

During the first experimental trial in [2] they report that "animals were receiving the audio electrical stimulus but did not know how to react to it. Some animals went in circles while the stimulus was applied. Others ran straight forward with their heads shaking." Research by Nolte et. al. [3] is on training deer to avoid places using similar control signals of electric shock and noise. They reported that deer learned to avoid areas associated with shock after certain training, but such effects did not persist long after shock devices were deactivated.

Research results [4~6] clearly show that we need a much better understanding of animal behaviour before we can correctly control their activities. It is difficult to achieve practical and reliable cattle monitoring with current conventional technologies due to challenges such as large grazing areas of cattle, long time periods of data sampling, and constantly varying physical environments. Wireless sensor networks bring a new level of possibilities into this area with the potential for greatly increased spatial and temporal resolution of measurement data. CSIRO has created a wireless sensor platform for animal behaviour monitoring where we are able to observe and collect information of animals without significantly interfering with them [7]. The sensors on the animal can collect information such as each individual's location, moving speed,

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temperature, 3-axis acceleration values, and 3-axis magnetic field strength. Based on such monitoring information, we can then learn each animal's behaviour and activities. Such activity classification can run on each sensor locally. We just need to transmit animal states over the radio if it is needed.

The next section describes animal behaviour understanding by analysing the datasets collected by the wireless sensor networks. We briefly discuss the hardware and the collected datasets, and then describe the animal behaviour analysis in detail. In Section III, we discuss the experimental results based on the observation datasets. We conclude with a summary of the results and discussion of future work in Section IV.

2. Datasets analysis based on wireless sensor networks monitoring system

2.1 Data collection

Livestock monitoring needs to be able to cope with animals' mobility and movement. As a result, communication links need to be able to deal with this mobility and be able to cover long distances between nodes. CSIRO ICT Centre's Autonomous Systems Laboratory has developed a wireless sensor network test bed for environmental and animal behaviour monitoring at an experimental farm covering three paddocks (see Figure 2). In the test bed, fixed environmental nodes are solar powered, and together with the mobile animal nodes, form a prototype for work on the "smart farm" of the future. The nodes used in these experiments are CSIRO developed *Fleck2* (120mm × 60mm) [7] devices (see Figure 1), with different sensor configurations, all running TinyOS and using Deluge for code download. The *Fleck2* was specifically designed for applications in animal tracking and control. It is a compact and low-cost wireless sensor hardware device with a diverse number of sensors including GPS, 3-axis acceleration, 3-axis magnetic field strength and temperature, as well as the ability to store considerable amounts of data.

The sensor networks can collect a large amount of sensoring data, including:

1) GPS information: Fleck2 ID, time, longitude, latitude.
2) Accelerometer and magnetometer information: *Fleck2* ID, gps time, m_x, m_y, m_z (three magnetometer measurement), a_x, a_y, a_z (three accelerometer measurement).
3) Navigation solution information: *Fleck2* ID, GPS time, X_{ECEF}, Y_{ECEF}, Z_{ECEF}, V_x, V_y, V_z. This dataset records the signal from GPS that uses Earth Centred, Earth Fixed Cartesian coordinates to define three dimensional positions. Its z-axis is pointing to the mean rotational axis of the Earth coincide; the x-axis is pointing to the mean Greenwich meridian, while the y-axis is directed to complete a right-handed system.

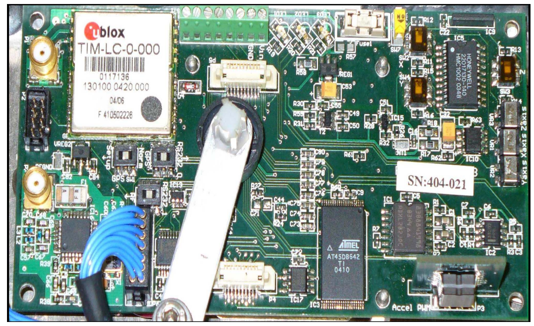


Fig. 1. The Fleck2 (120mm × 60mm). It has on-board a temperature sensor, 3 accelerometers, 3 magnetometers, and a GPS receiver.

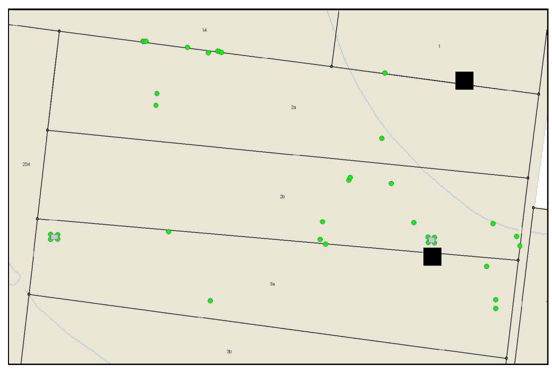


Fig. 2. Three paddocks as experimental testbed - 2a, 2b, 3a. Each paddock's size is around 100 meter by 600 meter. In each paddock, there were 15-cows + 15-calves (only five~six cows have the collar on). Small dots are trees. Two rectangles are water.

Our datasets came from six cows whose data were recorded during a four day period in May 2006. Each animal wore a smart collar consisting of a Fleck2, batteries and GPS and RF antennas. The collar goes around the animal's neck as in Figure 3. The *Fleck2* is located at the bottom of the cow's neck, hence the acceleration and magnetic field along x, y, and z-axis are fixed along the direction drawn in Figure 3.

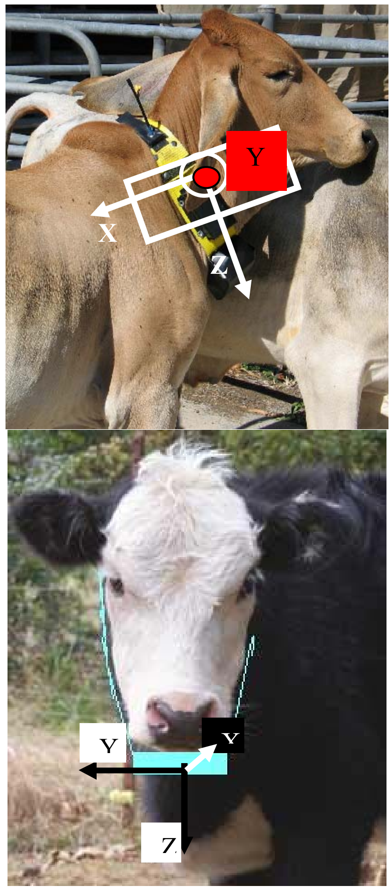


Fig. 3. The coordinate system corresponds to collars on animal. The board is located at the bottom of the cow's neck. x-axis - toward tail of cow; y-axis - toward right; z-axis - toward ground.

The raw GPS data can be stored, at the expense of memory, and be post-processed to yield very accurate position information. This provides rich information about the position of the animal and its activity. The current technology for achieving this is to observe the animals from a high tower using video or note taking, or to use GPS data loggers. The *Fleck2s* can transmit data in real-time over the animal-borne adhoc network as well as buffering significant amounts of data on-board. As mentioned in Introduction, the main aim of the research reported in this paper is to understand and classify individual animal activity states. To ensure the reliability, the data was stored in on-board flash memory and downloaded at the end of the experiment. Meanwhile, summary information is relayed out over the multi-hop network for online monitoring.

2.2 Data analysis for animal behaviour understanding

Animal's states can be classified into sub-classes according to different standards and purposes. To address the need by animal scientists within CSIRO, the state classes we are using are shown in Figure 4. In a hierarchical classification structure such as this, we start classification from the highest layer activities, that is, to identify between stationary and travelling states. The goal of future work is to classify the various activities in the whole structure.

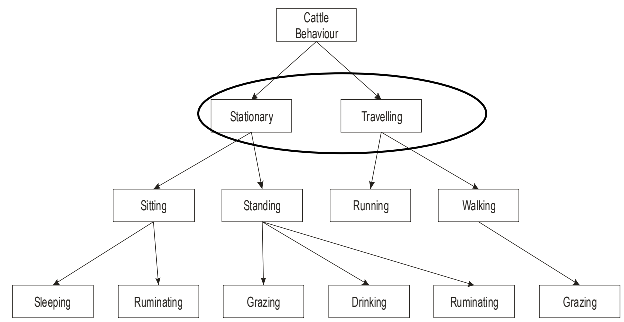


Fig. 4. One way to classify animal's activities. We start from identifying stationary activity from travelling activity.

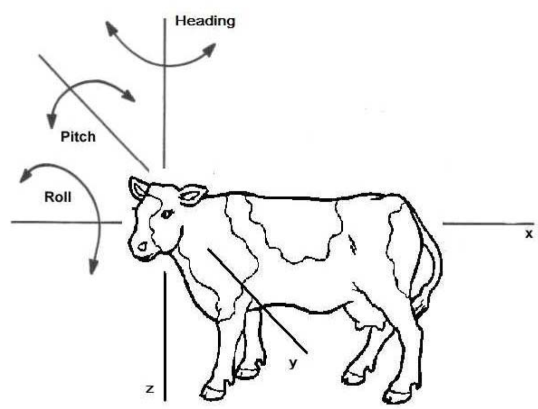


Fig. 5. Three angle definition: roll angle, Pitch angle and heading angle.

2.2.1 Dynamic body status of animals With all the datasets from Fleck2, we can record and analyse animal activities. The accelerometer and magnetometer signals allow us to determine the attitude of the Fleck2 on the animal from which we can determine the dynamic body status of the animals through three angles along the animal's head-neck region. These three angles, roll angle ϕ, pitch angle θ, and heading angle ψ, are defined as shown in Figure 5. From these angles, we can learn whether the animal's head is up or down, or which way the animal is oriented with respect to magnetic north.

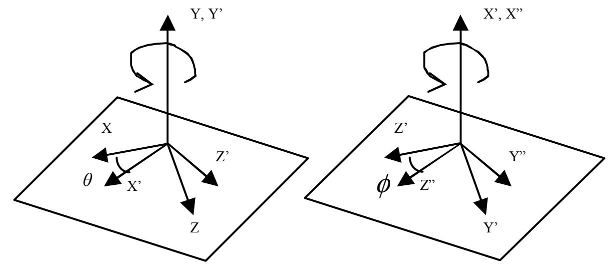
As shown in Figure 3, the orientation of the accelerometer and magnetometer axes are: x-axis towards back, y-axis out the side and the z-axis downward. The angles can be calculated accordingly as [8]:

1) Roll angle: $\phi = \arctan(\frac{a_y}{a_z})$;
2) Pitch angle: $\theta = -\arcsin(a_x)$;
3) To calculate the heading angle, the magnetometer measurement needs to be used. Firstly, the observed magnetic field needs to be rotated from the *Fleck2* frame to the Earth frame. That is,

$$\begin{bmatrix} E_{Bx} \\ E_{By} \\ E_{Bz} \end{bmatrix} = \begin{bmatrix} 1 & \sin(\phi)\tan(\theta) & \cos(\phi)\tan(\theta) \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi)/\cos(\theta) & \cos(\phi)/\cos(\theta) \end{bmatrix} \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix}, \quad (1)$$

where E_{Bx}, E_{By}, and E_{Bz} are the rotated magnetic measurement. The heading angle is then defined as: $\psi = -\arctan(\frac{E_{By}}{E_{Bx}})$. Note that overall magnetometer scale factor is not important because only a quotient is required.

2.2.2 Fleck2 frame rotation Ideally, the collar should be put on the cow's neck to have the *Fleck2* parallelised to ground. That is, one axis downward (e.g. x-axis) and the other two parallelised to ground surface (e.g. y-axis and z-axis). This is the assumption when we calculate roll angle, pitch angle and heading angle in above section. However we can see from Fig. 3 that the *Fleck2* is not in this ideal orientation in the realistic situation. Hence we applied a transformation to rotate the frame back to the ideal orientation. For such rotation, we use the average of the accelerometer measurements, $[\overline{a_x}, \overline{a_y}, \overline{a_z}]$, as an estimation of current realistic accelerometer orientations. To calculate the rotation angles, we assume the rotation took place from the ideal directions, with accelerometer value [1 0 0], to current directions, with accelerometer value $[\overline{a_x}, \overline{a_y}, \overline{a_z}]$. After we determine the rotation angles, an inverse rotation can then be applied to rotate the current frame to the ideal frame (see Fig.6).



(a) rotation around axis Y (b) rotation around axis X

Fig. 6. The 3-axis frame rotation to correct the measurement of accelerometer and magnetometer.

The rotation is done in two steps as in Fig. 6.

- First rotation around axis Y:

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix},$$

- Second rotation around axis X:

$$\begin{bmatrix} x'' \\ y'' \\ z'' \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi) & \cos(\phi) \end{bmatrix} \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix}.$$

Hence the desired rotation can be stated as

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi) & \cos(\phi) \end{bmatrix} \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \overline{a_x} \\ \overline{a_y} \\ \overline{a_z} \end{bmatrix},$$

where θ is the angle rotated along y-axis, and ϕ the angle rotated along x-axis. By solving the above equations, we can determine the values θ and ϕ. The rotated acceleration values $[a_x' \ a_y' \ a_z']$ can then be calculated as:

$$\begin{bmatrix} a_x' \\ a_y' \\ a_z' \end{bmatrix} = \left(\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi) & \cos(\phi) \end{bmatrix} \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \right)^{-1} \begin{bmatrix} \overline{a_x} \\ \overline{a_y} \\ \overline{a_z} \end{bmatrix}$$

2.2.3 Speed and Heading Angles using ECEF Signals Coordinates representing positions on the earth can be given in two formats, Spherical or Cartesian. The GPS receiver in *Fleck2* outputs the cows' position as spherical coordinates $[\varphi, \lambda, h]$. They are three dimensional components of latitude (φ), longitude (λ) and height above ellipsoid (h). With two of the components being non-linear with angular units, computations are more complex for coordinate geometry problems. Alternatively, Cartesian coordinates are entirely linear and provide for a much simpler mathematical platform. The origin and orientation of the Cartesian coordinate frame are dependent on the user's application and many well defined systems already exist. For global applications the system known as Earth Centred - Earth Fixed (ECEF) is preferred. As mentioned in Section II-A, the GPS receiver on *Fleck2* also outputs the ECEF signal, which includes the cow's location and moving speed along three axes in the ECEF XYZ reference frame. To convert these values to a local tangent plane (LTP), the velocity vector must be rotated using the following direction cosine matrix (North, East, Down) and solving for each component results in the following matrix transformation [9]:

$$\begin{bmatrix} V_{north} \\ V_{east} \\ V_{down} \end{bmatrix} = \begin{bmatrix} -\sin(\varphi)\cos(\lambda) & -\sin(\varphi)\sin(\lambda) & \cos(\varphi) \\ -\sin(\lambda) & \cos(\lambda) & 0 \\ -\cos(\varphi)\cos(\lambda) & -\cos(\varphi)\sin(\lambda) & -\sin(\varphi) \end{bmatrix} \begin{bmatrix} V_{X_{ECEF}} \\ V_{Y_{ECEF}} \\ V_{Z_{ECEF}} \end{bmatrix}$$

. The moving speed and heading direction can be derived from the velocity information using the following relationship:

$$v_{ECEF} = \sqrt{V_{north}{}^2 + V_{east}{}^2}\,, \tag{2}$$

and

$$\theta_{ECEF} = \arctan(\frac{V_{east}}{V_{north}})\,. \tag{3}$$

We can also use v_{ECEF} and θ_{ECEF} to judge animal's activities.

3. Experimental results and analysis

In this section, we discuss the experimental results based on the observation datasets from the sensor networks. The dataset analysis allows us to gain a broad understanding of what is possible with current wireless sensor network technology.

The dataset came from six cows with *Fleck2* collars that run during a four-day period from 3-7 May 2006. The GPS data was recorded at 4 Hz. The accelerometer and magnetometer data were recorded at 10 Hz. The data were collected when the animals were moving freely within a paddock within about 100m x 600m. GPS location error is less than 10 meters.

While the sensor network is collecting data, ground truth observations were also performed during 8am to 11 am on the 4th May 2006. The observation included two parts:

- Human observation records of animal activities in tables, classifying animal behaviour as defined in Fig. 4.
- 15 video streams recording animals' movement. From these video streams, one can recognise each cow's activities.

We will analyse the animal behaviour based on above information in the following parts.

3.1 Speed and heading angle calculation using ECEF measurement

Let us firstly calculate the animal's moving trace, speed and heading angles using ECEF signals. For instance, cow #1004 is analysed in this case. Fig. 7 shows the moving trajectory of it over the whole 4-day period.

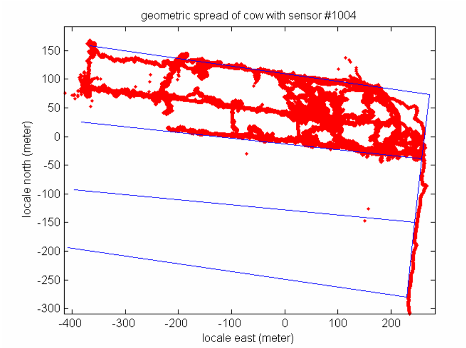


Fig. 7. The moving trajectory of cow #1004 over the whole 4-day period.

To view more clearly what is happening, we chose a half-hour period for cow #1004: 9:45am to 10:25am on 4th May 2006. The video streams and human observation record show that the cow's activities during this period are:

- 9:40am~9:58am: standing with grazing;
- 9:59am~10:08am: walking along the fence;
- 10:09am~10:34am: standing with grazing.

The moving speed and heading direction are calculated using equations (2) and (3). Fig. 8 shows the animal moving speed and the location along locale east and north versus time. By combining these three figures, one can see that the cow moved at very low speed most of the time. During about 9:59am to 10:08am, the cow moved towards a southeast direction at a quick speed (over 2 meter per minute). Fig. 9 shows the heading angle over the same period. A constant heading angle about -92^0 can be clearly seen over the quick moving period (9:59am to 10:08am). Over the "standing with grazing" period, the heading angles range between -180^0 to 180^0 as the animal moves its head in random directions.

Although we only show a short period of calculation results for one cow, the overall moving speed and heading direction results of all cows show a similar relationship. This experiment proves that we can use the ECEF measurement to classify animal's activity between standing and moving. One of our initial goals is thus achieved as expected.

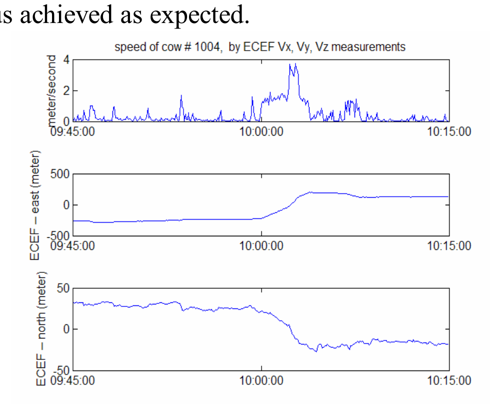


Fig. 8. Cow #1004 moving activities over 9:45am to 10:25am on 4th May 2006. Cow moved quickly during 9:59am ~ 10:08am. (a) Moving speed versus time. (b) Cow's location: east versus time. (c) Cow's location: north versus time.

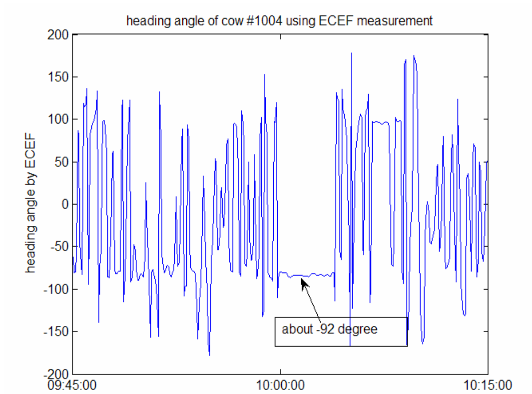


Fig. 9. The heading angle of cow #1004 using ECEF measurement. It keeps constant while the cow is walking along the same direction.

3.2 Angle calculation using accelerometer and magnetometer measurement

By using ECEF measurements, we can already classify the top level activities in Fig. 4. In order to understand the animal behaviour and multi-classify the animal activities in more detail (lower level in Fig. 4), it is clear the ECEF measurement does not provide enough information. Hence we need to look at the accelerometer and magnetometer measurements in the datasets as well.

In the following information analysis, the original acceleration values (in g) were filtered by a low pass filter to obtain DC components (and hence remove AC component). The reason we do so is that we believe the DC component corresponds to the rotation of accelerometer within the gravitational field. Animal movement, on the other hand, can be expected to correspond to the AC response. Because the maximum frequency of accelerometer is 10 Hz, the cut off frequency for the LP filter is set to be 1 Hz. To calculate the heading angles, the magnetometer measurements were also filtered by the same filter with the same cut off frequency. For this experiment, we chose two short periods for data analysis. These two periods both have good corresponding video streams that can be used for ground truth comparison.

3.2.1 Cow #1018: grooming and grazing while standing The first period dataset covers cow #1018 during 8:30am to 8:45am on 4th May 2006. The video streams and human observation records show that the cow's overall activity during this period is standing, with detailed activities as:

- 8:30am~8:35am: still standing;
- 8:35am~8:36am: standing with grooming;
- 8:37am~8:38am: standing;
- 8:39am~8:44am: standing / small distance walking with grazing.

Figs. 10-14 give a lot of details of the cow's movement. Firstly, Fig. 10 gives the moving trajectory showing cow #1018 stays very stable with near zero moving speed. Then in Fig. 11, we can clearly identify the cow's grooming during 8:35am using the AC components of accelerometer, which has bigger variance comparing to the still standing activity before 8:35am. It is highlighted by circles. We can also see that the variance increased again at 8:39am when the cow started grazing. It is highlighted by rectangles. On the other hand, the DC components of accelerometer, shown in Fig. 12, are neat signals response to the rotation of accelerometer. To calculate three angles, the Fleck2 frame is rotated using the methodology in Section II.

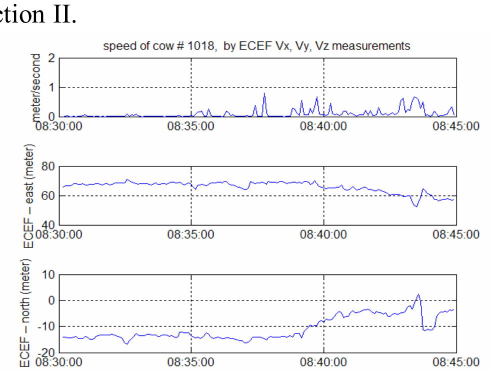


Fig. 10. Cow #1018 moving activities over 8:30am to 8:45am on 4th May 2006. Cow stands for most of the time. (a) Moving speed versus

time. (b) Cow's location: east versus time. (c) Cow's location: north versus time.**

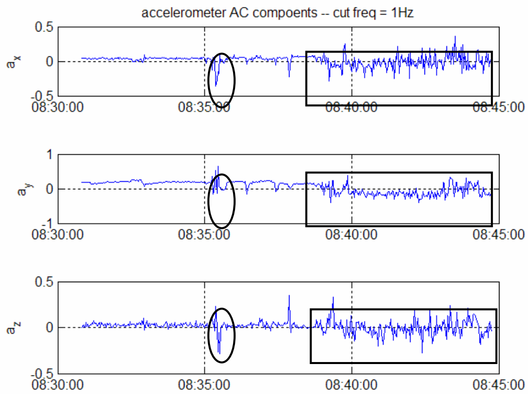


Fig. 11. Cow #1018 moving activities over 8:30am to 8:45am on 4th May 2006. The AC components of 3-axis accelerometer measurement with the cut-off frequency as 1Hz. Circles cover the grooming activity period. Rectangles cover the grazing activity period.

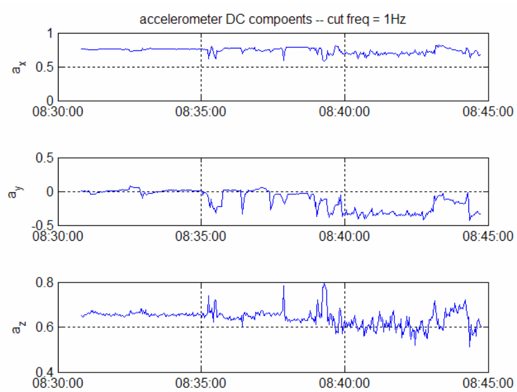


Fig. 12. Cow #1018 moving activities over 8:30am to 8:45am on 4th May 2006. The DC components with the cut-off frequency as 1Hz.

Fig. 13 gives the three angles that we are aiming for. Both the roll angle and pitch angle are small values which show that the animal cannot move with a large range in these two directions. For the grazing period (rectangular area), three angles vary quickly within small value ranges. For other activity periods, for instance, during 8:36am~8:39am, the angles keep very constant with only a small number of changes. One problem that we noticed is that the heading angle does not look realistic in that the changing range only covers [-20^0, 20^0]. This could be because of the error during the rotation of observed magnetic field from the *Fleck2* frame to the Earth frame in equation (1). We also calculate the gradient of heading angles, from which we can see the grooming and grazing behaviour periods can be identified clearly from standing behaviour period.

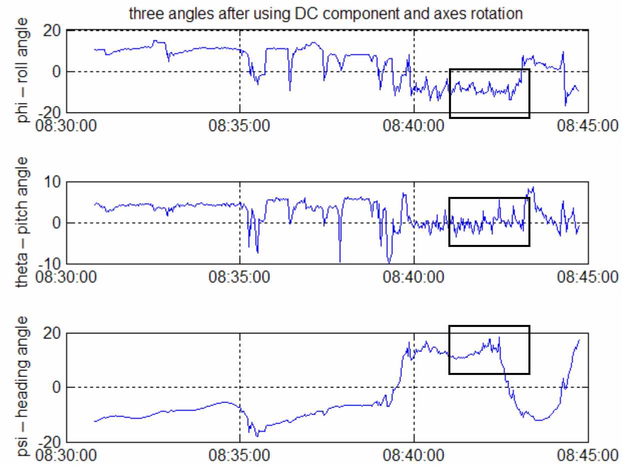


Fig. 13. Cow #1018 moving activities over 8:30am to 8:45am on 4th May 2006. Three angles calculated using DC components after the axes rotation. Rectangles cover the grazing activity period.

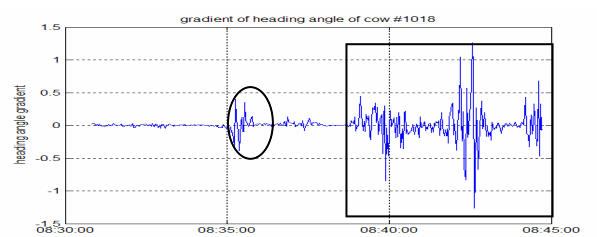


Fig. 14. Gradient of heading angles. Circles cover the grooming activity period. Rectangles cover the grazing activity period.

3.2.2 Cow #1008: sitting to standing The second period dataset is learnt because it covers cow #1008 activities changing from sitting to standing within two-three minutes. It is during 8:39am to 8:42am on 4th May 2006. The video streams and human observation records show that the cow was sitting for a while, then stood up at around 8:41am, and remained standing. If we start the analysis by looking at the ECEF signal, there is hardly any information included (see Fig. 15).

However when we look at the DC components of the accelerometer measurement, several sharp changes occur around 8:40am. The gradient of three angles also shows such activity clearly changing (see Figs. 16-17).

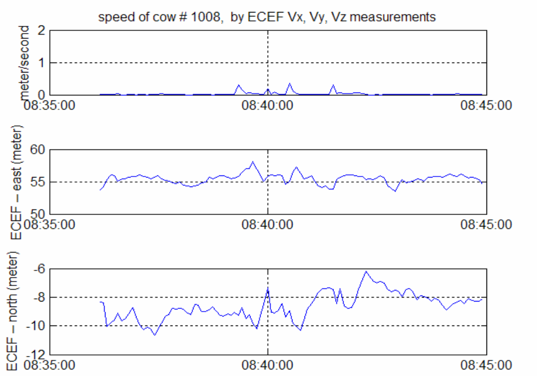


Fig. 15. Cow #1008 moving activities over 8:35am to 8:45am on 4th May 2006. Cow stays still. No information can be easily achieved using ECEF measurement.

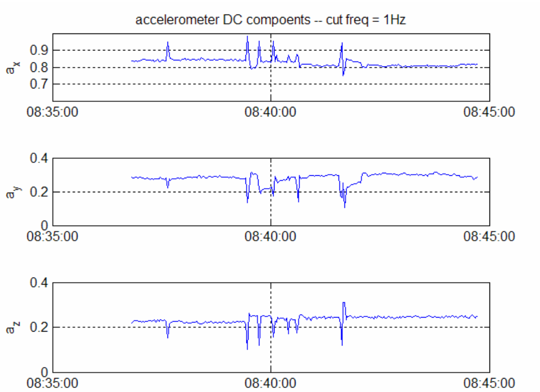


Fig. 16. Cow #1008 moving activities over 8:35am to 8:45am on 4th May 2006. The DC components record implies some activity changes.

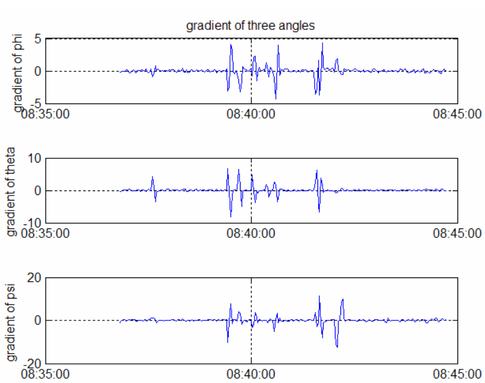


Fig. 17. Cow #1008 moving activities over 8:35am to 8:45am on 4th May 2006. The gradient of three angles shows that the cow changed its activity around 8:40am.

4. Conclusion

In this paper, we present current research on livestock behaviour understanding using a wireless sensor network monitoring system. The future goal of this research is to successfully control livestock movement and activities. One way to do so is to execute stimulus manually or with pre-set variable values, testing them with real animals, then use the test results to adjust the variables again. As each animal is different, such process is very slow and inefficient. A better way is to have a self-adaptive system running on each animal. The system can then adjust the variables according to observed data automatically in real time. Such control methodology can be built based on a wireless sensor network, where each node (sensor) can have a self-adaptive control strategy onboard based on the understanding of animal's behaviour. This design strategy can also cope with individual animal differences better than compared with the fixed stimulus across all animals.

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