Transforming Agriculture through Pervasive Wireless Sensor Networks

A large-scale, outdoor pervasive computing system uses static and animal-borne nodes to measure the state of a complex system comprising climate, soil, pasture, and animals.

griculture faces many challenges, such as climate change, water shortages, labor shortages due to an aging urbanized population, and increased societal concern about issues such as animal welfare, food safety, and environmental impact. Humanity depends on agriculture and water for survival, so optimal, profitable, and sustainable use of our land and water resources is critical. At

Tim Wark, Peter Corke, Pavan Sikka, Lasse Klingbeil, Ying Guo, Chris Crossman, Phil Valencia, Dave Swain, and Greg Bishop-Hurley CSIRO Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO), we're developing a "smart farm" that applies wireless sensor network technology to animal agriculture to address these requirements. We've created a pervasive, self-configuring network of cheap,

simple devices that learn about their environment and seek to control it for beneficial purposes.

How sensors can help

The agricultural practices brought to Australia from Europe have turned out to be poorly suited to a land with different seasonal patterns, hydrological and nutrient cycles, and geology. As in other countries where the land has been overexploited, these practices have led to problems such as soil erosion, declining water quality, loss of biodiversity, and salinity. These problems are generally interlinked: Overgrazing in an inland region can lead to increased erosion. The increased sediment runoff can harm the distant Great Barrier Reef, or reduced water runoff can reduce the recharge of

underground aquifers. Sensor networks are a critical tool for measuring and understanding the complex coupled dynamics of natural systems.

In the past, farming was a labor-intensive human activity that involved tending plants and animals on an almost individual basis. Modern agriculture, in contrast, is highly mechanized and involves very large areas per farmer. For instance, in the UK, 200,000 farms disappeared between 1966 and 1995, and 17,000 farmers and farmworkers left the land in 2003. In the US, between 1950 and 1999, the number of farms decreased by 64 percent. The global demographic shift in farm labor and reduced recruitment of younger people has created an aging farming population and looming labor shortage. The consolidation has resulted in less personalized care and attention to both animals and landscape. It has also achieved a major cost savings, but at the risk of undesired situations arising and being overlooked until it's too late—for instance, until the land is degraded or disease outbreaks occur. Prevention, as always, is the best strategy. A sensor network can improve productivity by increasing situational awareness of the state of the pasture and animals.

Animal production also requires controlling animals' locations—traditionally by using fences and mustering. Studies show that fence installation and maintenance and mustering constitute approximately 30 percent of the total cost of rearing an animal. However, these expensive, static assets might actually hinder rather than promote ideal landmanagement practices. Areas of marginal land become inaccessible because it's not cost-effective

Figure 1. A solar-powered node showing energy received and consumed over six days: (a) a typical solar cell generates from 80 to 400 kilojoules of solar energy monthly, and (b) the solar and battery voltage and current is more than adequate for our system.

to fence and use it. Mustering in remote areas is dangerous—undertaken by people on horseback or motorbikes or in helicopters—and labor shortages are affecting this as well. Mobile sensor network nodes can monitor and influence animals' positions in the landscape. You can find more details about our motivations and work at www.sensornets.csiro.au.

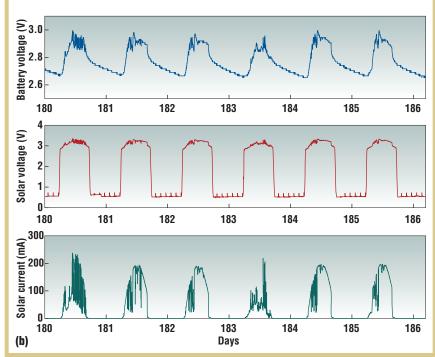
Sensor network platform

Outdoor sensor networks must be able to tolerate harsh conditions to survive long-term deployments. A key aspect of our work has been developing a robust hardware platform for outdoor use. Inspired by the original Berkeley mote, we've developed three generations of devices since 2002: the Fleck-1, Fleck-2, and Fleck-3.

These devices incorporate numerous design features that make our platform ideal for long-term outdoor deployments: a Nordic radio with a range of over 1 km that operates on the 433-MHz (Fleck-1 and Fleck-2) or 915-MHz (Fleck-3) band, an integral solar battery-charging circuit, and an extensive range of sensors and sensor interfaces. The Fleck-3 also incorporates a real-time clock chip to reduce microcontroller overheads. Our software stack is based on the TinyOS software stack with a custom component for the radio.

We use this platform for both static and mobile nodes. Static nodes are based on the Fleck-1,² which consists of an Atmega 128 microcontroller running at 8 MHz, a Nordic NRF903 radio transceiver with a bit rate of 76.8 Kbits per second, and an onboard temperature sensor. These nodes are connected to soil moisture sensors or custom complementary metal oxide semiconductor (CMOS) camera modules.





In a sunny environment such as Australia, solar energy is clearly the most abundant environmental energy source. Research groups are becoming increasingly interested in the use of solar energy, and numerous recent platforms harness it.^{3,4} However, these platforms have typically only been tested over short time periods.

We developed our Fleck-3 platform concurrently with many of these platforms, and we've been one of the earliest groups to exploit solar power for long-term sensor network deployments.² Figure 1a shows a typical (10,000 mm²) solar cell we've used in our deployments. Experiments have shown that these panels can generate from 80 to 400 kilojoules of solar energy each month, an order of magnitude more than our current applications require. Figure 1b shows a typical example of battery and solar voltage and current, where the minimum battery voltage (2.7 V) is well above the 1.1 V the Fleck requires.

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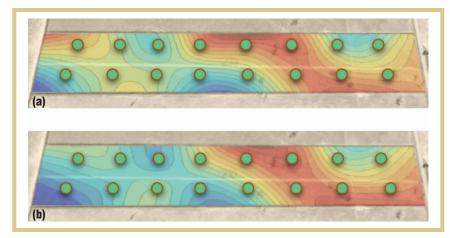


Figure 2. A color-coded contour plot of soil moisture. Blue regions indicate higher soil moisture and red regions indicate lower moisture. Green dots indicate the sensor nodes' locations. See www.sensornets.csiro.au for live data.

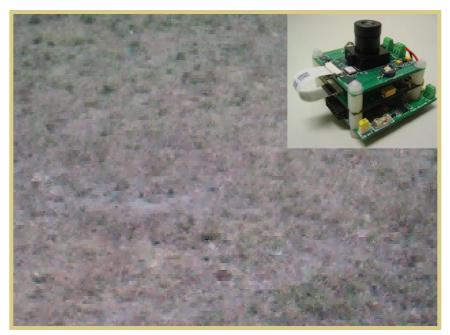


Figure 3. A Fleck-1 pasture image with camera stack (inset). Packet loss is approximately 30 percent for this image.

The mobile node, the Fleck-2, is a Fleck-1 base augmented by a variety of motion sensors. It contains an onboard triaxial electronic compass coupled with three orthogonally mounted accelerometers as well as an onboard GPS receiver. An 8-Mbit flash chip augmented by a multimedia card socket can support up to 512 Mbytes of onboard storage using an MMC flash memory card. Newer-

generation static and mobile nodes (which we're currently deploying) are all based on the Fleck-3.

Sensor networks for pasture assessment

Knowing the state of pastures and crop fields in a farm environment is crucial for farmers. As weather patterns change, crops mature, and cattle graze pastures for food, farmers must decide when to irrigate pastures, apply fertilizer, or move cattle to another pasture. Typically, a farmer relies on a combination of experience, visual observation, and intuition as to when to make such decisions, but they will almost certainly be far from optimal.

As such, the agricultural-research community has become increasingly interested in the use of sensor networks for agricultural monitoring and has undertaken numerous pilot projects. A cropmonitoring sensor network, Lofar Agro, sassessed potato crop quality. Nodes measured temperature and humidity, then multihopped the data back to a gateway. Carnegie Mellon University researchers developed a small network for measuring the state of a plant nursery, with sensors measuring humidity and temperature at various points in the nursery.

We have concurrently focused on sensor networks as a means for providing a new level of information about the state of pastures. Our initial experiments have revolved around the use of solar-powered moisture nodes and low-resolution camera nodes for pasture assessment. Given these two complementary information sources, we can reach a new understanding of the pasture's underlying state.

Measuring soil moisture

Our soil moisture nodes use commercially available ECH₂O capacitance-based sensors that measure the surrounding soil's volumetric water content. These sensors generally don't require calibration and have an error of +/– 2 percent. The network automatically takes readings, typically at one-minute intervals, from each node and sends them back. Data is aggregated at the base to give an up-to-date moisture profile for the whole pasture.

Figure 2 shows an example of data from a six-hectare pasture fitted with 16 soil moisture nodes attached to wooden

Figure 4. Attaching sensor nodes to cattle: (a) the sensor coordinate system fits inside a plastic box, which (b) fits into the pocket of a collar around the animal's neck.

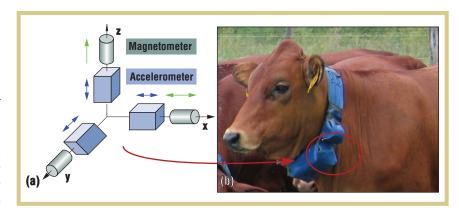
posts mounted in the ground at equal intervals. Using a spline-interpolation technique over the individual moisture readings from each node, we estimate the function describing the whole pasture's soil moisture profile. You can clearly see the effects of irrigation at the pasture's left end (figure 2a is unirrigated, 2b is irrigated), as well as natural variation across the pasture. This is valuable input to a predictive pasture growth model.

Pasture camera nodes

Other important parameters for farmers include surface grass coverage or grass height. We're investigating the potential for completely self-contained, self-powered camera nodes that can send images over our low-bandwidth networks. The inset photo in figure 3 shows an example of our camera, which we created by stacking a Fleck-1 board with a custom-designed Texas Instruments DSP board and a custom CMOS camera board. You can also connect a separate MMC board to the stack for storing images.

The Fleck mainboard, DSP board, flash memory board, and camera board work together to take an image and store it in local flash memory. A camera manager at the base preallocates time slots for each camera to send its image, which is reconstructed at the base. A program at the base interpolates missing packets.

Figure 3 shows a typical pasture image that we can obtain. This image contains a useful amount of information about the degree of grass coverage, grass height, and greenness level. In this image, you can clearly see the change in the greenness, which correlates well with the amount of soil moisture variation that nodes are measuring in this same pasture. Ongoing work is investigating image-processing techniques that can take place at the node to extract the pas-



ture's parameters, making the information more compact to transmit. We can also use cameras to observe cattle at water troughs and gates.

Cattle sensor networks

Cattle are an integral part of this dynamic system. By better understanding cattle's individual and herd behavior, grazing habits, and interactions with the surrounding environment, farmers and animal scientists can potentially select for desirable qualities that were previously hard to measure or not fully understood.

One of the first major uses of wireless sensor networks for animal monitoring was in tracking zebras as part of the ZebraNet project.⁷ In this system, animal GPS position data, taken every few minutes, was hopped in a peer-to-peer fashion to other animals when they came in range. Subject to the amount of storage space on each device, a user could then download historical position data from multiple animals by approaching a single zebra. Researchers have since proposed more sophisticated systems for ad hoc routing of data through large networks of mobile cattle nodes.8 However. this work is still at the simulation stage.

Systems such as ZebraNet have focused on the transfer of historical position information between nodes. Our work in animal sensor networks, however, has focused on extracting information (such as behavior states) that helps farmers understand how herds of cattle interact and graze pastures. This can help solve the agricultural problem of finding better ways to use limited pasture resources.

Another unique focus, which we discuss in more detail later, has been on the potential for internode communication to provide contact-log information (that is, a log of the number of times a pair of animals come into proximity of each other) without needing position information. Animal researchers can use this information to determine characteristics such as cow-calf relationships over time or trends in herd behavior.

Collars and other hardware

To attach sensor nodes to cattle, we created custom collars for them to wear² (see figure 4). We mounted the Fleck-2 board and the expansion stimuli board inside IP55-rated plastic (ABS) boxes measuring $130 \times 90 \times 60$ mm. These boxes fit into the pocket of a specially designed webbing collar that went around each animal's neck. The collar also had pockets for the two batteries and GPS and radio antennas. Future devices would be miniaturized, but the current collar designs are robust and well suited for experimentation.

An important consideration of the collar design was protection against damage by cattle. The initial collar design had a quarter-wavelength (20 cm) whip antenna standing vertically from the top of the collar, which is optimal for communication. In practice, the cattle consistently destroyed the antenna within hours, either by rubbing against trees or cooperating with others to chew them off. Our current, nonoptimal solution is to lay the radio frequency antenna flat along the top of the collar.

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Figure 5. The probabilities of cattle receiving pings for varying distances apart with bin sizes of 10 m.

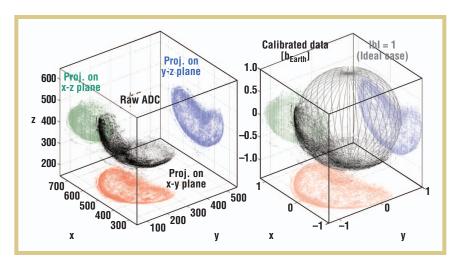


Figure 6. An illustration of the means by which magnetometers can be self-calibrated automatically from data generated from cattle movement. By using a magnetic field sensor model that considers offset, sensitivity, nonorthogonalities of the axis, and disturbing magnetic fields, all raw sensor readings should lie on the surface of an ellipsoid (assuming a constant Earth's magnetic field vector in the volume of interest). The calibration aims to collect enough readings while the cow is moving and to fit an ellipsoid to these data to extract the calibration parameters.

Communication

We've aimed to answer two main questions regarding sensor networks:

- 1. Can we reliably send and receive packets between mobile cattle nodes (for example, multihop routing of behavior states)?
- 2. Can we extract valuable information from each node's position and iner-

tial information so as to determine animal and herd state?

To answer the first question, we tested the performance of a typical peer-to-peer cattle sensor network using a group of 13 cows fitted with Fleck collars⁹ (see figure 4). Cows were placed in a single 100 × 600 m pasture for four days. All collars pinged each other once a minute, with each ping containing an animal's GPS position and time of each ping transmission. To allow subsequent analysis, all ping data was saved to multimedia cards on each Fleck device.

The graph in figure 5 shows the likelihood of animals receiving pings as a function of their distance from each other. We determined this by calculating the density functions of interanimal distances combined with statistics about ping reception. We calculated results only for distances up to 210 m apart, beyond which there were too few samples. Our results show an interesting near-field effect relating to the suboptimal way in which the antennas are mounted. This means that when cattle are extremely close together, the communication performance is worse than when cattle are a little farther apart. As cattle move farther apart, the communication throughput oscillates somewhat, with an overall trend of degradation as distance increases. These are important parameters to consider when designing distributed algorithms.

Comparing these results to the ZebraNet communications results is difficult because the systems use different radios and antenna types (ZebraNet uses a dipole antenna). In particular, the ZebraNet results⁷ are from manual range tests rather than being based on

Figure 7. Scatter plots showing the relationship of animal speed to accelerometer signal magnitude area for various behavior classes at (a) day and (b) night.

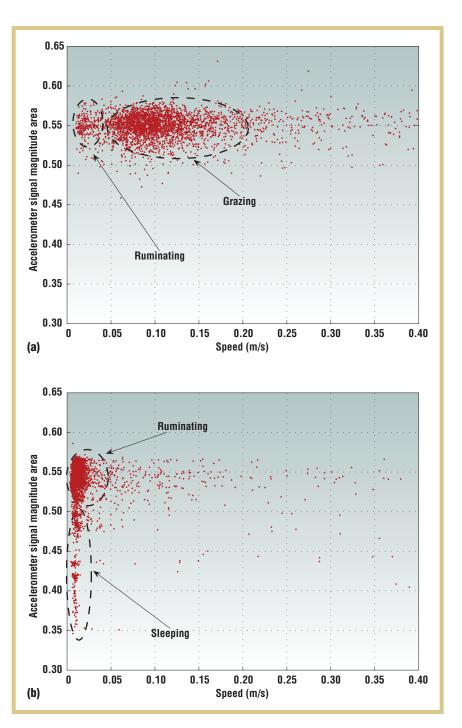
actual results from collars mounted on moving animals, where signal absorption into the animal becomes a critical factor. This is a key aspect of the results we present in figure 5.

Behavior classification

The ability to model herd and individual behavior is important in providing additional information that can help optimally manage livestock and environmental resources. A major focus of our work has been on methods for modeling cattle's individual and herd behavior on the basis of position and inertial data from the wearable Fleck-2 collar.

Calibrating the inertial sensors is crucial to making the best use of this sensor information. For example, accelerometer data should range between 0-1 g. We've developed a calibration method based on the actual data from each animal that doesn't require performing specific calibration routines for each device. The method is based on building a model of the expected distribution of inertial data and fitting model parameters to each data set. Figure 6 shows the raw readings of the magnetic field sensors during two hours of normal cow movements, where an ellipsoid model is fitted to the data. We used a similar principle to calibrate the acceleration sensors, using the gravitation vector as a reference in this case.

By combining position information with inertial information, we can extract numerous features and use them to estimate cattle's behavior states. We can derive features such as speed, turning rate, pitch of head, and movement energy from inertial sensors. Figure 7 shows feature plots of animal speed (as derived from GPS data) versus accelerometer signal magnitude area. Figure 7a shows features during the day when the animal was quite active; figure 7b shows features at



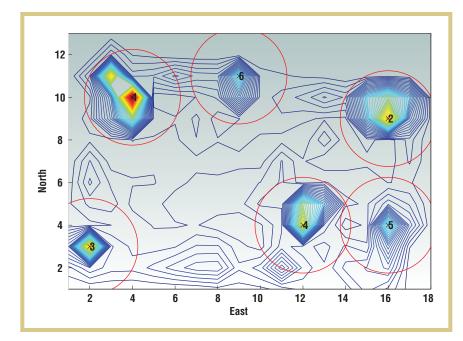
night when activity was limited. Given empirical data derived from numerous hours of video and human observation data, we can see how behavior states such as sleeping, grazing, and ruminating (chewing the cud) appear as clear clusters in the feature space. We've observed these clusters to be consistent over a range of animals over time, meaning we

can build fairly generic models.

We've been investigating statistical classification techniques (beyond this article's scope) that let us automatically determine behavior state from such features. Figure 8 shows an example of the areas where a herd of cattle was classified as grazing over four days. As you can see, cattle graze pastures in a nonhomogeneous way,

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meaning careful planning of pasture areas is necessary to prevent local overgrazing and problems such as land erosion.

We're undertaking additional work to investigate integrating radio frequency identification tags with sensor networks. More and more cattle in Australia have unique RFID tags on their ears. We're using this unique information to record an ID, along with the amount of food a cow eats at supplementary food stations. As a result, we can track each animal's exact grain intake and send it over the network.

Behavior control

Aside from monitoring the environment, a remaining challenge is to control animals in the landscape—actuation. Actuation could take the form of automatically controlled gates, water troughs, and feeding stations. More interestingly, it could involve applying various stimuli to the animals to influence their motion. 10-12 This work is in its early stages, but preliminary results are encouraging. (CSIRO adheres to the Australian Code of Practice for the Care and Use of Animals for Scientific Purposes and operates in compliance with all relevant animal welfare legislation.) Unlike more conventional implementations of robotic multiagent systems, animal agents aren't perfectly controllable. Their full state—including both spatial position and mental state, such as stress, desire, hunger, or mood—is difficult to measure, and their behavior depends on factors such as age, season, temperature, and food availability.

e now have field-proven hardware and software and considerable experience in applying sensor networks to this problem space. We're working to greatly increase the deployed network's scale to hundreds of static and mobile nodes. We can measure the system's state at a level of detail that was previously impossible. It's entirely possible to record where every mouthful of grass has been taken from, as well as where and how quickly future pasture growth will occur. We're also starting to integrate information from remote sensing that complements on-the-ground measurements.

We're now poised to explore how adjusting resource utilization to resource availability in near real time might close the loop on environmental impact. We believe it's possible to create a large-scale, distributed, and heterogeneous control

Figure 8. An example of the behavior of grazing cattle over four days. Contours of equal occupancy show clear 2D position clustering of grazing regions $(10 \times 10 \text{ m})$ for six cows.

system that employs teams of sensors, people, water, pasture, animals, and perhaps robots. Perhaps this will be the next agricultural revolution.

ACKNOWLEDGMENTS

We thank Les Overs, Stephen Brosnan, Graeme Winstanley, and John Witham for their assistance in hardware development and Katrina Tane, Chris O'Neill, Belmont Farm manager Rob Young, and Belmont Research Station staff for their assistance with the experimental work.

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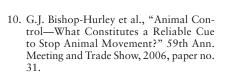
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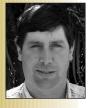
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