

# A smart ear-attached sensor for real-time sows behavior classification



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#### **1. Introduction**

• Short battery life limits the applicability of wearable sensors in animal behavior monitoring.



• The aim of this research was to develop an ear-attached acceleration sensor of low power consumption for sow health and welfare related studies.



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#### 2. Material and methods

#### 2.1 Sensor design

• The wireless acceleration sensor was composed of a low power three-axis accelerometer, a Bluetooth and an

PCB antenna.





Fig. 1. The wireless acceleration sensor block diagram (top), front of the PCB (bottom left), back of the PCB with battery in the case (bottom center), and the case cover (bottom, right).





## **2.2 Wireless monitoring system design**

- A wireless monitoring system was designed to perform field experiments on sows.
- It included multiple wireless acceleration sensors, a Bluetooth receiver, a serial

device server, and a database server.





#### 2. Material and methods

#### **2.3 Sensor operation modes**

- In the continuous mode, the sensors read and transferred the acceleration data at a fixed frequency of 1 Hz.
- In the data-grouping mode, the sensors read all the acceleration data at 1 Hz and saved them in a memory for transmission.
- The power saving mode was designed to minimize the number of data for transmission by excluding the data when a sow was not in movement.



Fig. 3. Program flow diagrams of the continuous mode (left top), data-grouping mode (left bottom) and power saving mode (right).



### **2.4 Data saving threshold determination**

- A threshold was set to control whether the sensor should save a set of acceleration data after reading the data.
- A simple method to analyze a threshold setting with a first-order different acceleration of three typical sow behaviors. This was realized by comparing the current dataset with the previous dataset using Eq. (1).

$$\Delta a_i = \left| a_i - a_{i-1} \right| \tag{1}$$

• The dataset at each time was not saved in the storage for transmission unless its first-order difference exceeded a pre-defined threshold.

If  $\Delta a_i \ge \Delta a \rightarrow Save \ for \ transmission$ If  $\Delta a_i < \Delta a \rightarrow Do \ nothing$ 



#### 2. Material and methods

#### **2.5 Laboratory test of the sensor**

 A laboratory test was conducted to determine the power consumption of the sensors at the three different working states, i.e., sleeping, reading, and broadcasting.





#### **2.6 Field test of the monitoring system on sows**

- Eight wireless acceleration sensors were attached to eight sows in the two rooms.
- The sensor cases were glued to the RFID eartags using a cyanoacrylate glue.
- Continuous video recordings were also made to monitor the behaviors of the eight sows individually 24 h a day.



Fig. 4. An acceleration sensor is attached to the RFID ear-tag on a sow.



#### **3.1 Sensor performance**

- A sow was usually more active during two major periods on a day, in the morning from 4:00 to 10:00 and in the afternoon from 14:00 to 21:00.
- The behaviors of a sow before farrowing was noticeably different as detected by the acceleration sensor.
- The wireless sensor could be effectively used for monitoring and predicting sow farrowing.



Fig. 5. Two typical days of acceleration data measured on two sows. Top: typical activities of a sow. Bottom: activities of a sow on the day before farrowing at 2:00 AM the following day.



#### **3.2 Current and energy consumptions in three sensor working states**

• All the current peaks of approximately 1.8–4.9 mA for a duration of 100 ms were



Fig. 6. An example of currents of the sensor at three working states.



#### **3.2 Current and energy consumptions in three sensor working states**

• The energy consumptions during the sleeping and data reading states were only

0.5 and 1.9%, respectively, of the total. The broadcasting state consumed as

much as 97.6 % of the total power consumption.

• This demonstrated that the sensor battery life could be significantly extended if

the power consumption in the broadcasting state could be reduced.

Table 1. Mean current and energy consumptions of the three operating states based on three days of measurements on sow behaviors.

<b>Operating state</b>	Current (mA)	<b>Operation time (ms)</b>	<b>Energy consumption (%)</b>	
Sleeping	0.00213	738	0.5	
Data reading	0.037	162	1.9	
Broadcasting	3.03	100	97.6	





#### **3.3 Data saving threshold**

**3.3.1 Characteristics of accelerations and three sow behaviors** 

- The first-order different acceleration was near zero for the data recorded during sow resting.
- The differences between the two adjacent sets of acceleration data were mostly very small.

Fig. 7. Typical acceleration waveforms of a sow at resting (top left), moving (middle left), and eating (bottom left). First-order different accelerations of a sow at resting (top right), moving (middle right), and eating (bottom right).





#### **3.3 Data saving threshold**

 The averages of mean-moving and mean-eating in three axes were 0.162 g and 0.184 g, respectively. The difference between two adjacent acceleration data of these two behaviors were more than 0.162 g. By averaging 0.043 g and 0.162 g, an optimal threshold of approximately 0.1 g was obtained.

Table 2. Standard deviations (STD) and mean values of the first-order difference related to the three behaviors in three typical days of acceleration data.

	Axis (g)				
Statistics	Х	Y	Z	Average (g)	
STD resting	0.14	0.059	0.226	0.142	
STD moving	0.251	0.322	0.478	0.35	
STD eating	0.209	0.207	0.32	0.245	
Mean-resting	0.055	0.029	0.044	0.043	
Mean-moving	0.154	0.147	0.184	0.162	
Mean-eating	0.154	0.171	0.226	0.184	



#### **3.3 Data saving threshold**

- 3.3.2 Optimal data saving threshold
- In the 0-1 g range of first-order differences for the three behavioral conditions, the proportions of 0-0.1 g in the X-, Y- and Z-axis for sows at resting were 86%, 97.5%, and 93.5%, respectively.
- Therefore, the sensor was programmed to send an acceleration dataset if any first-order difference of the three axes was greater than 0.1 g. This could save up to 86% of battery power.



Fig. 8. Distribution of number of data versus first-order differences for a sow at resting shown in Fig. 7 top right.



#### **3.4 Current consumptions at three sensor operating modes**

 Analysis of the field test data revealed that the average mean number of broadcasts per day at power saving mode was only 8.7% of that at the continuous mode, and 52.2% of that at the data grouping mode for the six sows.

Sow number and operating mode	Number of broadcasts (n d <sup>-1</sup> )	Average current (mA)		Battery lifetime (d)	
<b>#1-6 continuous</b>	86400	0.3	311	31	
#1-6 data-grouping	14400	0.0	)58	183	
#1 power saving	10204	0.04	435	220	
#2 power saving	9419	0.0408		234	
#3 power saving	6104	0.0292		328	
#4 power saving	6807	0.0	316	303	
#5 power saving	5957	0.0287		333	
#6 power saving	6644		0.031		_
Mean for #1-#6 power saving	7523	0.0	)34	288	

Table 3. Analysis of average currents of the three operating modes for six sows.





#### **4.1 Conclusions**

(1) Acceleration data of the sows revealed three major behaviors (resting, moving, and eating) and there were variations in the time durations of these behaviors among different sows.
(2) Data broadcasting of the sensors consumed 97.6% of total energy at the continuous operating mode and the battery life was only about 31 days.
(3) The average battery life could be extended to about 288 days at power saving

mode when the first-order difference threshold was set at 0.1 g.



#### 4. Conclusions

#### **4.2 Future improvements**

- Develop an algorithm to adopt dynamic thresholds;
- Optimize data reading frequencies to balance between battery life and animal behavior study requirement;
- Upgrade the acceleration sensors to behavior sensors by using on-sensor intelligent data analysis.





