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Deployment and Evaluation of an Active RFID Tracking System for Precision Animal Management

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DEPLOYMENT AND EVALUATION OF AN ACTIVE RFID TRACKING SYSTEM

FOR PRECISION ANIMAL MANAGEMENT

by

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Modern swine facilities were developed mainly based on logistics of feeding and moving animals. In recent years, however, the public has become increasingly concerned about animal care and well-being. A better understanding of the animal space utilization in current facilities could lead to improved facility design and better animal well-being. This study was conducted to determine whether an active RFID tag tracking system could accurately provide animal locomotion data on an individual animal basis. The system is composed of four sensors, located in the corners of a swine pen, and compact tags, which attach to the animals and transmit a signal. The sensors use the tag signals to determine 3-D positions in real-time. A data acquisition system was developed to capture raw data from the system software into a database for analysis. A single-location test was performed with 34 tags placed in close proximity to a known location, followed by three trials of a second test with 34 tags randomly arranged in a 1-meter by 1-meter grid across the pen. Results from the single-location test were relatively consistent with the manufacturer's claim of 15 cm accuracy. Error was much higher in the three trials of the grid test, particularly in the Z-direction. The system was used to track four pigs for a period of two days, with visual data analysis showing 84.4% tracking accuracy. Finally, the system was used to track animals from different genetic lines and temperaments.

Statistical analysis of this data indicated significant differences in movement data with regard to sex of the animal, genetic lineage, and temperament scores, particularly in distance traveled and time spent near the feeder and nipple drinkers. Further work revealed that the system is prone to generate large, random jumps in the data that need to be filtered if the desired use is for instantaneous measurements. Without data filtering, the system would be best suited for monitoring hourly or daily average values for animal movement parameters.

Acknowledgements

I would like to express my sincere gratitude to my advisors, Dr. Deepak Keshwani (Department of Biological Systems Engineering, UNL) and Dr. Tami Brown-Brandl (US Meat Animal Research Center) for their continued support and encouragement through this process. Throughout this project, I faced many new challenges for the first time in my academic career, and I truly felt that they wanted to see me succeed in overcoming these obstacles.

Second, I would like to thank Dustin Dam (Systems Integration Engineer, Department of Biological Systems Engineering, UNL) for his assistance in developing our data collection service, which was critical for this project to succeed.

Next, I would like to thank Dr. David Jones (Associate Dean, College of Engineering, UNL) for acting as a member of my graduate committee and providing his valuable time and insight in reviewing this thesis.

Furthermore, I would like to extend my deep appreciation to the employees in the swine unit at the US Meat Animal Research Center for welcoming me to their place of work, and providing much-needed assistance to the city boy who looked more than a little lost in a swine pen.

Finally, my greatest thanks to my family, friends, and girlfriend, without whose love and support I surely would not have seen this through to the end. I am forever grateful.

Dedication

To the life and memory of my late friend, Reece Abraham Benesch. This probably makes me the first person to dedicate a thesis on livestock production to a devoted vegetarian. Fortunately, I think he would find that as funny as I do, and that thought makes me happy. I miss him every day.

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CHAPTER 1

A REVIEW OF PRECISION LIVESTOCK FARMING

1.1 Overview of Swine Production

Pigs have played an important role in the production of food and animal-based products, such as soap, since their domestication. The versatility of pigs and pig products has allowed the swine industry to evolve and remain competitive in agricultural enterprise on a global level (Moeller and Crespo, 2015). Today, pork is the most widely consumed meat in the world. Traditionally, lard was used in cooking and in many household products, so pigs with a balance of fat and muscle were desirable. However, as animal fat became less useful, feeding for conversion to muscle mass became the primary focus of swine production, leading to the much leaner hogs seen today (U.S. EPA, 2015).

Prior to the 1960s, most swine production operations were small and based on open lots or pasture systems. Over the last 50 years, these operations have followed a long-term trend toward fewer and larger operations. In the last 15 years alone, the number of hog farms has been reduced by 70 percent. Meanwhile, the majority of U.S. pigs are now raised in confinement operations with more than 5000 animals (Giamalva, 2014). Developments in housing and manure management strategies have allowed for the enclosure of large operations in confined buildings with controlled environments. The main advantage of a controlled, confined production environment is the ability for year-round swine production (USDA, 2016) as well as improved food safety and animal well-being. Over the years these larger, more efficient operations have made it difficult for smaller farms to remain profitable. Geographically, the large operations tend to be concentrated around major feed sources, usually corn and soybean, as feed costs are the greatest expense in hog raising operations. As a result, the Midwestern and Southeastern states are the major pig producers in the U.S. (USDA, 2016).

The United States is the third largest producer and consumer of pork products, accounting for roughly 10 percent of global production. The U.S. is the largest exporter of pork and a relatively small importer, as most U.S. pork is consumed domestically. Additionally, the U.S. is the largest importer of live swine and a small exporter. The majority of these are wean-to-finish pigs, as well as a large number for direct slaughter and consumption (Moeller and Crespo, 2015).

Generally speaking, there are three types of operations in today's swine industry: farrow-to-finish, farrow-to-wean, and wean-to-finish. In farrow-to-finish operations, hogs are raised from birth and sold at slaughter weight (~250 pounds). Farrow-to-wean hogs are raised from birth to a specified weight (between 10 and 60 pounds) and then sold to a finishing operation. Wean-to-finish operations purchase the wean hogs and grow them to be sold at slaughter weight. Generally, large operations tend to specialize in only one phase of production (Chiba, 2004). Some producers use a continuous flow production system, in which animals continuously arrive and leave a particular phase. Many producers opt for all in, all out (AIAO) systems, in which a whole group of pigs moves from one phase to the next, with gaps in between for building cleaning and maintenance. AIAO systems offer improved control of disease spread and reduced animal stress as a result of the smaller number of interactions with new animals from other populations (U.S. EPA, 2015).

The swine industry is presented with challenges and opportunities on several fronts. Animal health and welfare is of major concern, particularly as the trend continues toward larger farms in confined building. Ethical questions have arisen with increased public exposure to industrialized livestock production. These questions often regard the space afforded to animals in gestation stalls and farrowing crates, or the docking of tails for the prevention of tail biting. These practices have played a key role in increasing production efficiencies, so any new legal requirements would have a major impact on pig production. The underlying question is: How do we provide animal care on and individual basis in the face of progressively larger swine operations?

Environmental sustainability is another other major concern for the future of the swine industry. The geographical concentration of progressively larger swine operations will continue to cause problems with odors, water quality, and air quality that must be sustainably managed. Additionally, demands for feed will continue to increase, but the amount of arable land delegated to feed production will not. Increasing feed efficiency will be crucial for maintaining swine production.

Going forward, livestock producers will continue to be challenged by the rapidly increasing demand for food by a growing global population. Producers must continue to lower overhead costs and increase production efficiencies to remain competitive. Doing so will require a greater understanding of the physical and biological processes involved on all levels of livestock production.

1.2 Introduction to Precision Livestock Farming

As long as global population continues to grow, food production industries will constantly be challenged to cope with the proportional increase in demand for safe and sustainable food. The projected global population of 9.1 billion by 2050 will consume around 70 percent more food than in 2007, according to a 2009 report by the Food and Agricultural Organization of the United Nations (FAO). The report indicates a corresponding increase in meat production of 200 million metric tons by 2050 to compensate for the growth. Moreover, the concept of "safe" and "sustainable" food sources adds a layer of complexity to the increase in demand, presenting a unique set of challenges to each major food production industry.

The livestock production industry is facing increased pressure from multiple sources. Public exposure to livestock management methods has led to more intense scrutiny of animal care and well-being. Ethical questions often regard the living space afforded to animals and their treatment in confined operations. In pig production, for example, these include the size of gestation stalls and farrowing crates, or the docking of tails for the prevention of tail biting. Additional health concerns have been raised about the widespread use of antibiotics to combat the spread of disease among confined animals, and to promote muscle growth in cattle, swine, and poultry. Overuse of antibiotics can lead to antibiotic resistant bacteria, some of which can affect human health.

Between ethical concerns raised by the animal rights movement and the potential implications of meat animal treatment on human health, improving animal welfare has become a major hurdle for sustainable livestock production (Berckmans, 2014). With the rapid expansion of the industry, the labor force has struggled to produce enough employees well trained in animal husbandry, making it difficult to provide care on an individual basis while the number of animals per pen continues to increase. Minimizing the treatment of livestock with antibiotics, particularly those that show correlations with human pathogens, will also be necessary as the medical field struggles to combat antimicrobial resistance in bacteria (Mathew, 2007). Simultaneously, animal waste and gas production poses threats to soil, air, and water quality that must be sustainably managed (Berckmans, 2014).

If the livestock production industry is to remain economically competitive, farmers must address these challenges while continuing to lower overhead and improve production efficiencies. The industry has recognized that optimizing livestock production will require an understanding of the complex interaction between the physical and biological processes involved (Wathes 2008). Precision livestock farming (PLF) applies sensors and modeling techniques to livestock systems and aims to provide real-time information on individual animals in a large group setting. This information could be used to track a range of factors important to animal management, including feeding behaviors, drinking behaviors, access to cooling methods, resting time, specific animal interactions, growth, and reproduction.

1.3 Precision Livestock Farming Techniques

According to Wathes (2008), “PLF requires (i) continuous sensing of the process responses (or outputs in the terminology of the process engineer) at an appropriate frequency and scale with information fed back to the process controller; (ii) a compact, mathematical model, which predicts the dynamic responses of each process output to variation of the input(s) and can be – and is best – estimated on-line in real time; (iii) a target value and trajectory for each process output, e.g. a behavioural pattern, growth rate or pollutant emission; and (iv) actuators and a model-based predictive controller for the process inputs."

Recent research in precision livestock farming has focused primarily on establishing and evaluating sensor-based data collection techniques on livestock operations. Robust and affordable technologies have begun to emerge during this time, expanding the possibilities for continuous sensing of animal outputs (Berckmans 2014). Affordability of sensing and computing equipment has been a challenge for PLF, but basic biological sensors, cameras and microphones continue to become more affordable and improve in quality. Adequate storage for large data files is more widely available, and computing power continues to improve, making cameras and microphones particularly powerful tools for PLF research. Systems based on image, video and audio capture are referred to as remote sensing systems. These systems are advantageous, as they minimize disturbance to the animals and often eliminate the need for sensing units for each individual (Wathes 2008). However, the problem with image, video, and audio is that it is difficult to discern individuals out of a group.

Pigs in confinement are highly prone to bouts of aggressive behavior, often culminating in tail biting, which can lead to animal stress and serious injury (Oczak, 2013). Aggressive interactions between growing pigs in confinement have been analyzed using top-down (or overhead) video recordings (Oczak, 2013 and Viazzi, 2014). Manual labeling of aggressive interactions is possible but takes considerable time (Oczak, 2013). Converting video to image sequences and using image feature extraction software allows for aggressive behavior classification to be automated with 89 percent accuracy (Viazzi, 2014). Furthermore, image processing methods has been used to determine individual animal identity by marking animals with ink patterns (Kashiha, 2013), allowing for identification of resting behaviors. Image processing can also be used to determine thermal comfort (Shao, 2008) and other indicators of animal well-being, but is limited by the number of animals in a pen.

Microphones offer more opportunities for continuous remote sensing of physical, behavioral, and psychological characteristics. Speech recognition software can be adapted to analyze cow calls, translating calls to text messages indicating the condition of the cow (Jahns, 2008). Similarly, analysis of resonant frequencies of cow calls can be used to identify distinct types of psychological stress (Ikeda, 2008). Through a variety of modeling techniques, it is possible to detect cow calls associated with hunger, separation from calf or mother, oestrus (heat), labored breathing, and coughing (Jahns, 2008 and Ikeda, 2008). Coughing is an important indicator of illness in both humans and animals and is an early symptom associated with several diseases (Guarino, 2008). Like image analysis, sound analysis can be applied to any livestock animal. Field tests of cough detection algorithms have been performed in pig houses, as well (Guarino, 2008).

Many precision livestock farming techniques utilize sensors that make direct contact with the animal. Pedometers have been used to detect oestrus in cattle (Brehme, 2008). Automatic detection of fertile animals will aid livestock farmers in optimizing reproduction. Automatic weighing systems have been in place for some time (Wathes, 2008). In addition to monitoring weight, some feeder scale systems can now measure behavioral characteristics (Gates, 2008), including feeding duration, total intake, and frequency. Load sensors have been used during cattle milking to detect not only body weight, but load distribution on each leg (Pastell et al., 2008). Load distribution data can serve as an early indicator of hoof injuries, leg injuries, and lameness.

The applications given in this review are only a broad sample of data collection and interpretation techniques. In addition to continuous monitoring of animal outputs, environmental information is also an important factor in determining overall animal health at a given moment. Fortunately, environmental data is easy to collect, particularly in confined livestock systems. Relatively cheap sensors for continuous monitoring of temperature, humidity, air quality, etc. are available and can be helpful in identifying sources of animal stress.

1.4 Limitations

Ethical issues will continue to be a hurdle for the livestock industry, because optimizing food animal production will always involve balancing animal welfare with economic return. In other words, the most economically favorable process will likely not always be the most ethically favorable. Public perception of precision livestock farming will also be important. There is public opposition to mechanized animal management, and precision livestock farming could be viewed as furthering the treatment of animals simply as production systems. It is possible that system failures could lead to animal harm, and system reliability must be balanced with cost if PLF is to be feasible.

1.5 Future Perspectives

Advances in technology over the last 5-7 years have helped researchers develop reliable animal monitoring systems while cutting costs associated with sensing equipment. Researchers must strive to continue optimizing system performance and balancing costs, as economic feasibility will ultimately determine whether companies choose to invest at the large scale. PLF systems that scale up easily will fare better with investors. Most of the current research on PLF is geared toward collecting reliable data and creating data-based predictive models to link physical parameters with biological parameters. If PLF is to be successful, researchers need to develop more robust models that can handle the interactions of multiple physical and biological parameters, and provide meaningful outputs to farmers in real-time.

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CHAPTER 2

DEPLOYMENT AND EVALUATION OF AN ACTIVE RFID TRACKING SYSTEM FOR PRECISION ANIMAL MANAGEMENT

2.1 Introduction

Food production industries will constantly be challenged to cope with increased demand for safe and sustainable food. The projected global population of 9.1 billion by 2050 will consume around 70 percent more food than in 2007, according to a 2009 report by the Food and Agricultural Organization of the United Nations (FAO, 2009). The report indicates a corresponding increase in meat production of 200 million metric tons by 2050 to compensate for the growth. Moreover, the need for “safe” and “sustainable” food sources adds a layer of complexity to the increase in demand, presenting a unique set of challenges to each major food production industry.

The livestock production industry is facing increased pressure from multiple sources. Between ethical concerns raised by the animal rights movement and the potential implications of meat animal treatment on human health, improving animal welfare has become a major hurdle for sustainable livestock production (Berckmans, 2014). With the rapid expansion of the industry, the labor force has struggled to produce enough employees well trained in animal husbandry, making it increasingly difficult to track health parameters and provide care on an individual animal basis. A reliable solution to this problem has not been established. If the livestock production industry is to remain economically competitive, farmers must address this challenge while continuing to lower overhead and improve production efficiencies.

Radio-frequency identification (RFID) technology is a powerful tool for tracking the location of objects in real time. In an active RFID system, battery-powered tags are attached to the objects to be tracked and sensors are placed around the tracking area. The tags emit a signal at a specified time interval, which is received by the sensors and used to calculate the 3-dimensional position of the tags. We hypothesized that an active RFID system applied in a swine facility would provide accurate positional data on individual animals over time. Therefore, the first objective of this study was to deploy and evaluate an active RFID system within a swine facility to determine positional accuracy and ability to track individual animal movement. The second objective of this study was to determine if the system can detect differences in activity level and space utilization based on genetic lineage. The third objective was to determine if the system can detect differences in activity level and space utilization based on temperament scores.

2.2 Materials and Methods

2.2.1 Site and Equipment Setup

The active RFID tag tracking system (Real-Time Location System, Ubisense Inc., Denver, CO) was deployed in a swine pen in a finishing facility at the USDA Meat Animal Research Center in Clay Center, Nebraska. The pen had dimensions 6.33 m (W) × 5.09 m (L) with 1 m high fences and contained one five-hole feeder, four nipple drinkers, and a spray cooling system along the width of one side. A diagram of the swine pen, including key elements, can be found in Appendix A. The Real-Time Location System (RTLS) is composed of two hardware elements: sensors (Series 7000 Sensor, Ubisense Inc., Denver, CO) and tags (Series 7000 Compact Tag, Ubisense Inc., Denver, CO), shown in Figure 2.1. The sensors are placed around the perimeter of the desired tracking area and face inward. Tags are attached to the objects to be tracked, and transmit an Ultra-Wideband (UWB) signal, which is received by the sensors. According to the Ubisense RTLS training materials, at least two sensors need to receive a tag signal to calculate location. Two sensors provide five pieces of information to the position calculation algorithm: the azimuths for each sensor, the height of each sensor, and the time difference of arrival of the signal between the sensors. When more sensors receive a tag signal, more information is passed into the position calculation algorithm, yielding a more accurate tag position. This process is illustrated in Figure 2.2. (Ubisense Limited, 2014)

For this study, four sensors were mounted in the corners of the pen at a height of 2.2 meters and oriented toward the center of the pen, angled downward at 30 degrees. The sensors were connected to each other by cat6e Ethernet cables for the calculation of the difference in signal arrival time between each sensor. The sensors were also connected by cat6e Ethernet cables to a power-over-Ethernet (PoE) switch, for transmitting power and data to a computer (PowerEdge T320, Dell) (Figure 2.3). Water proof backings with cable glands (IP67 Sensor Backplate, Ubisense Inc., Denver, CO) were added to the sensors to prevent water and dust from damaging the cable connections.

Figure 2.1 Ubisense Series 7000 Sensor (top) and Series 7000 Compact Tag (bottom).

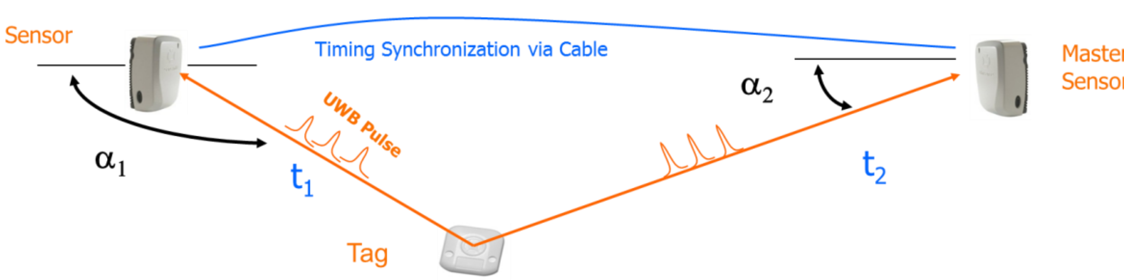

Figure 2.2 Illustration of how the active RFID system works. Tags are attached to the object of interest and emit a signal, which is received by the sensor and used to calculate position. Only two sensors are

shown here for simplicity, but the setup for this study uses four sensors. (Image: Ubisense Limited. (2014). Ubisense RTLS Training-Overview [PowerPoint Slides])

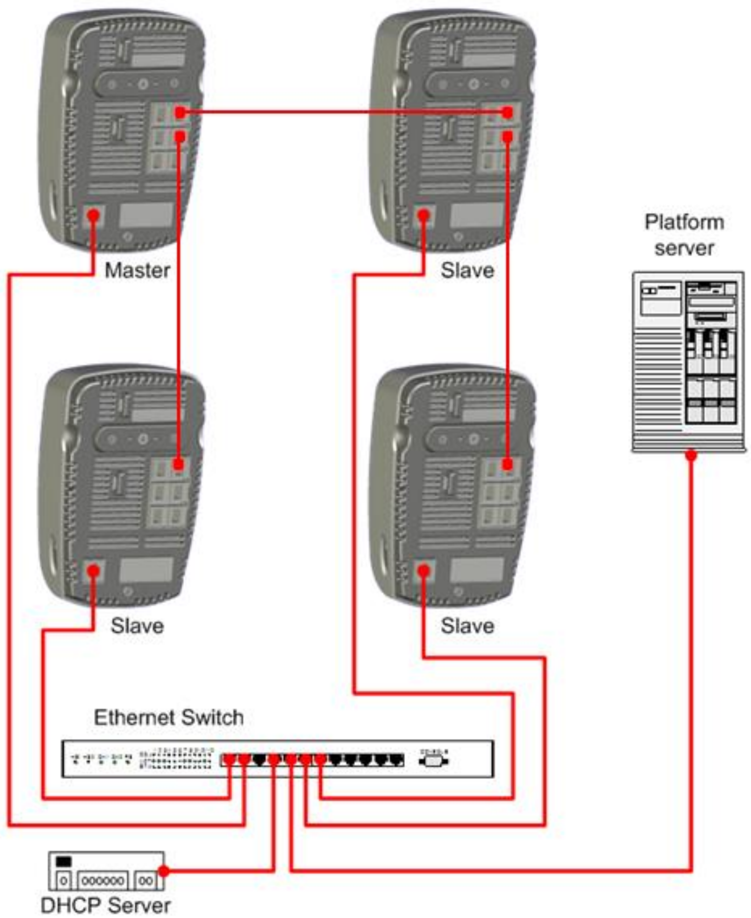

Figure 2.3 Diagram of the Ubisense RTLS system connections. Red lines represent cat6e Ethernet cables. The platform server and DHCP server are software services that run on the PC and support the Ubisense operating system. (Image: Ubisense Limited. (2014). Ubisense RTLS Training-Overview [PowerPoint Slides])

The Ubisense Smart Factory software (Ubisense Inc., Denver, CO) was used to calibrate the sensors to the shape and size of the swine pen. The system tracks and displays the last known position of a tag at a user-defined time interval, which is set by altering the update rate within the Ubisense software's data filtering options. The system is also capable of tracking when tags enter and exit certain zones within the tracking area, which are created by the user within the Location Engine (Figure 2.4). This project required the logging of tag locations and entry/exit event data, so a custom software service was developed to intercept the tag data from the Ubisense software and store it in a MySQL database for later download and analysis (Figure 2.5).

This application required that the system be able to run for undetermined durations and collect data for that entire time. Due to the long unknown durations of runtime, storage of data in simple files was determined to be inadequate. The potential for very large files and the volatility of the environment added additional risk for corruption or data loss. In accordance with best practices, a piece of server hardware (Dell PowerEdge T320) was procured to run the system. Advantageous features of this hardware include redundant power supplies and RAID6 storage array to enhance robustness. The software installed on the system includes Windows Server 2008 R2, Ubisense software suite, MySQL Server as well as a custom written Windows service. The custom Windows service simply registers for events that are available via the Ubisense .NET API and subsequently populates two different tables within the MySQL environment. One table is populated with tag location data, and the other with entry/exit event data.

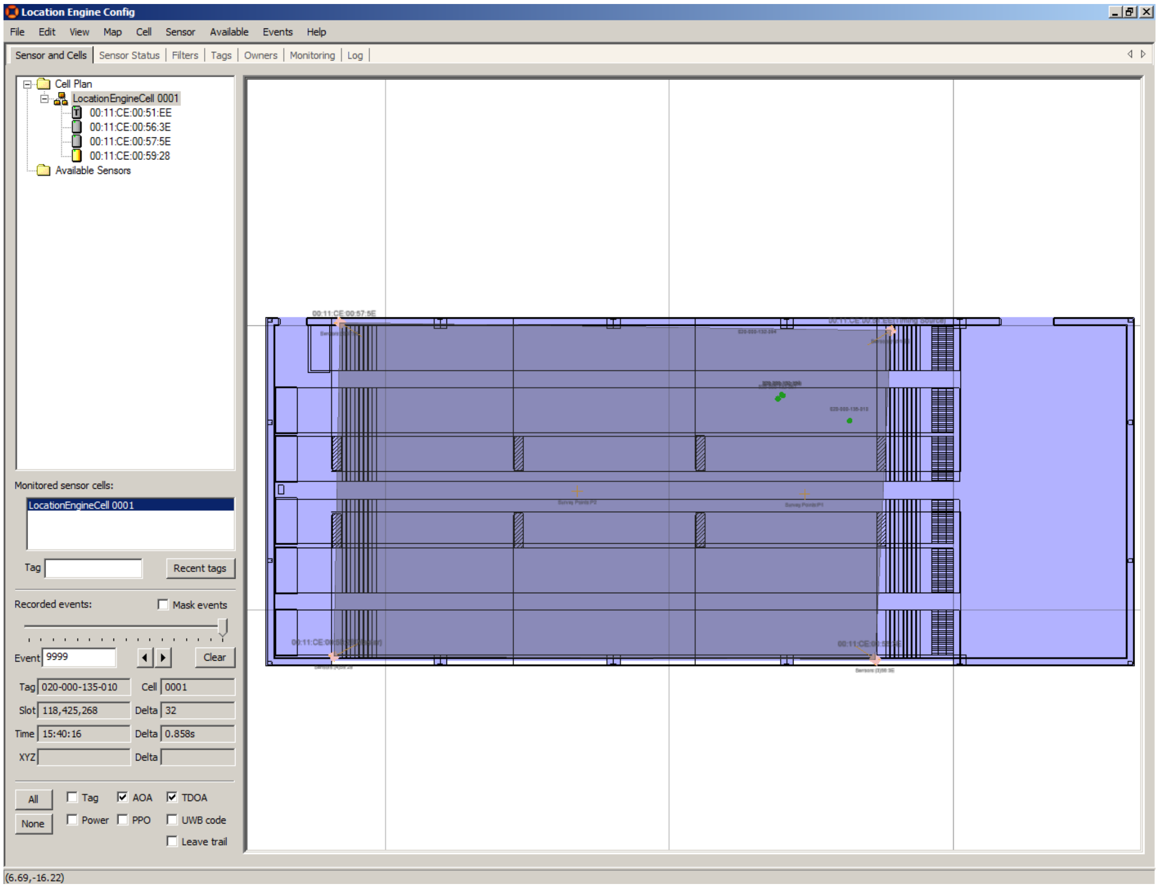

Figure 2.4 Ubisense Location Engine. The Location Engine provides tools for the setup and calibration of the tracking area. Additionally, it displays the last known position of active tags in real time and allows the user to monitor zone entry/exit events (known as spatial relations in the software). (Screenshot)

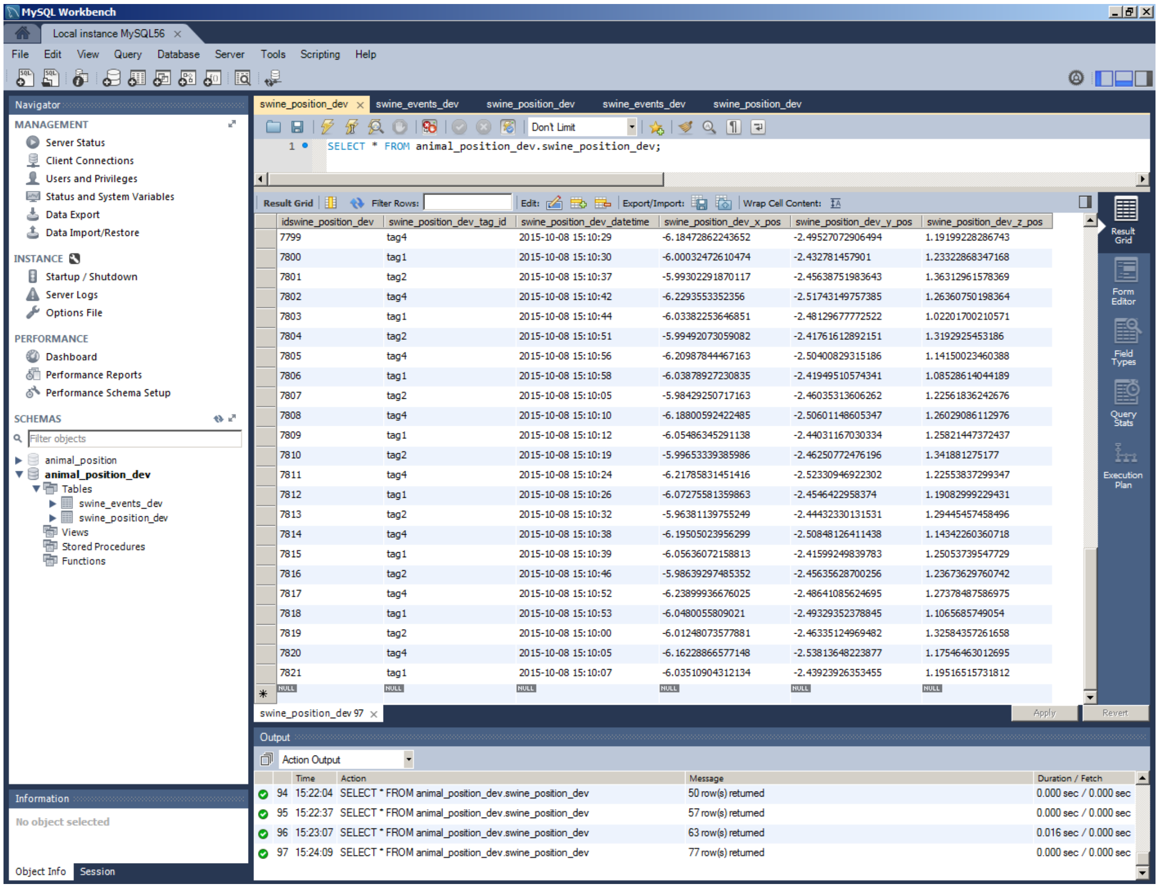

Figure 2.5 MySQL Workbench provides a graphical interface for the user to view, manage, and export data stored in a MySQL database. (Screenshot)

2.2.2 Stationary Tag Tests

Two tests were performed to evaluate the ability of the system to accurately locate stationary tags in the pen. Each pen holds a maximum of 40 animals, and 34 tags were used for tracking. For the first test, all tags were grouped together on a flat cardboard box in a 6×7 array, which was set on top of a bucket measuring 0.39 m in height (Figure 2.6). The bucket was centered on a single known location within the pen, and data were collected for one hour with tags updating positions every 15 seconds.

Figure 2.6 Setup for the single location test. Tags were placed on top of a bucket measuring 0.39 m in height, so that the tags would not be directly on the floor.

For the second test, boards were placed on top of buckets to create a 1 m × 1 m grid across the pen at a height of 0.39 m (Figure 2.7). The second test was performed three times, ensuring that each location on the grid was tested at least once. Also, performing three trials provided a way to distinguish whether any tracking issues at a given grid location were related to the tag placed at that location or if the issues were specific to that location in the pen. Each trial of the second test was performed with tag locations updating every 15 seconds for 24 hours.

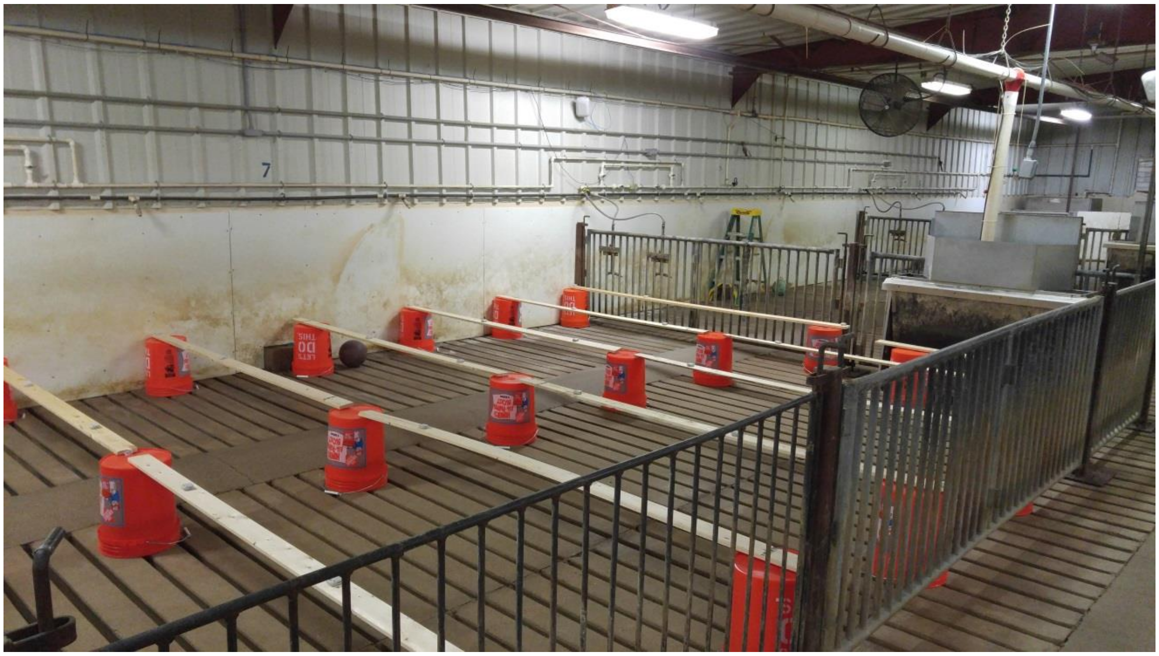

Figure 2.7 Setup for the grid test. Columns of buckets and boards were spaced 1 m apart, and tags were placed in 1 m intervals along the boards to create a grid.

For each test, the absolute error and standard deviation of the error of measured tag locations in the x, y, and z directions was calculated. Absolute error was calculated by subtracting the actual position from each measured position, and taking the absolute value. The Euclidean distance for each measured position was calculated using the formula:

$$E_{dist} = \sqrt{X_{err}{}^2 + Y_{err}{}^2 + Z_{err}{}^2} \qquad \text{(Eq. 1)}$$

Where E_{dist} is the Euclidean distance, X_{err} is the error in the X direction, Y_{err} is the error in the Y direction, and Z_{err} is the error in the Z direction. For this application, the Euclidean distance is a linear distance by which the measured tag position is displaced from the actual tag position. During analysis of the first test, the actual location of each tag was adjusted by the distance of the tag from the center of the array.

2.2.3 Mobile Tag Test

To test the ability of the system to locate the animals in the pen, four finishing gilts were tagged and tracked over two days. The tags were small enough (38 mm × 39 mm ×16.5 mm) to fit on the pigs' ears. It was desirable to have the tags near the head of the animal, so custom ear tag enclosures were printed using a 3D printer (Airwolf 3D, Costa Mesa, CA) (Figure 2.8 and 2.9). The enclosures were printed from NinjaFlex (NinjaTek, Manheim, PA), a thermoplastic elastomer. NinjaFlex was chosen for the combination of flexibility and durability it provided. After starting the print, it took roughly two hours for the printer to build up the back of the enclosure and the walls, at which point the tag was slipped in to the enclosure. It took approximately one hour for the printer to complete the top of the tag, leaving the tag completely sealed from the surrounding environment. It is worth noting here that the UWB signal emitted by the tags is minimally affected by passing through plastic or similar materials. In general, only passing the signal through a water-based medium has a detrimental effect on the tag signals (personal communication with Ubisense service representative, July 8, 2014).

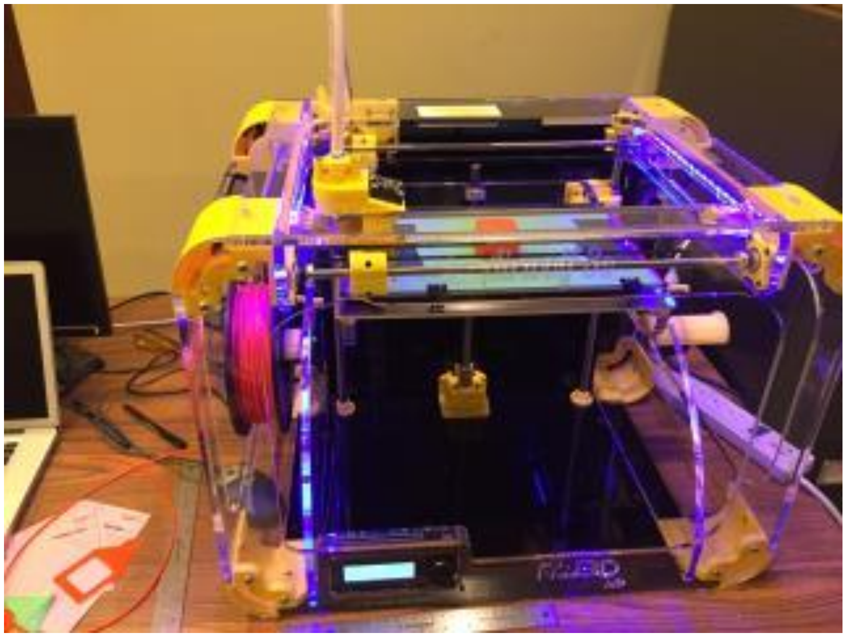

Figure 2.8 Airworld 3D printer used to print tag enclosures from NinjaFlex filament.

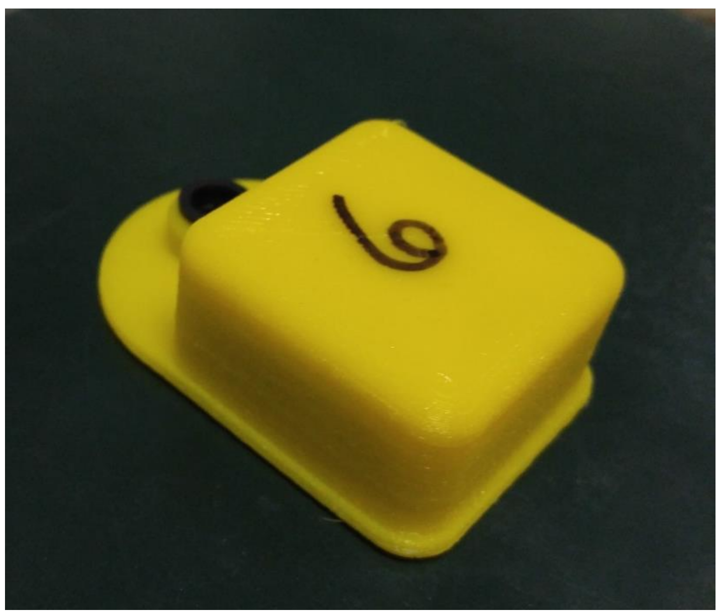

Figure 2.9 A completed 3D printed tag enclosure. A small plastic insert was added to the point of attachment to prevent the NinjaFlex material from stretching around the pin that attaches the tag to the ear of the animal.

During the test, three cameras were programmed to take pictures along the X axis and Y axis of the pen once per minute, and the pigs were marked with distinct patterns for visual identification (Figure 2.10). Three cameras were needed, as two were required to capture the full x-axis view. Colored tape was used to mark off 1 m intervals on the railings or wall in the foreground and background of images along the X and Y axis. This process established thirty 1 m × 1 m zones in the XY plane, with columns labeled A through F and rows 1 through 5 (Figure 2.11). Three sets of images per hour were selected where each pig was clearly visible in a zone, at times when the pigs appeared to be stationary. The corresponding location data at the time of each image were then compared to the images for verification of accurate tracking.

Figure 2.10 Example image along the Y axis of the swine pen. The orange tape marking 1 m intervals can be seen on the railings in the foreground and background.

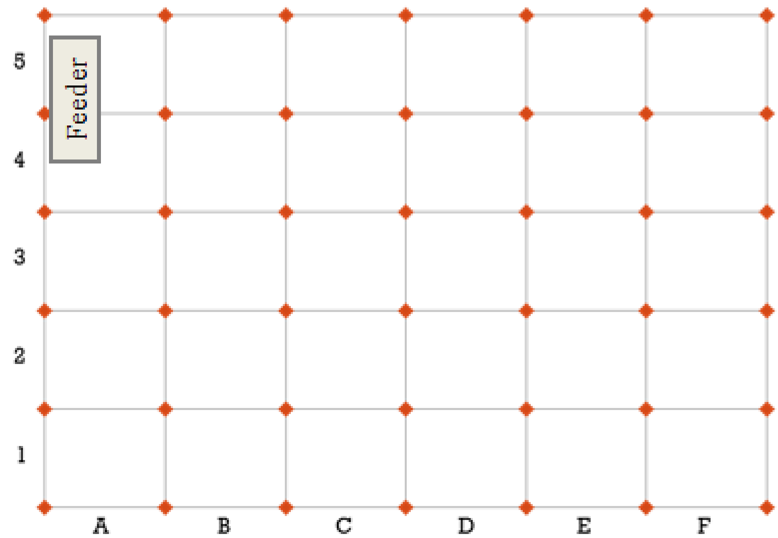

Figure 2.11 Thirty 1 m × 1 m zones were established by marking 1 m intervals along the X and Y axes and then capturing images along those two axes. The feeder is shown in gray as a point of reference.

2.2.4 Tracking Animals from Three Genetic Lines

For this test, a total of 18 pigs were tagged and placed in the pen, including six each from the Duroc, Yorkshire, and Landrace sire lines. During the first trial of this test, nine of the tags were chewed and disabled, so replacement tags were 3D-printed into enclosures for a second trial. Data were then collected for five full days, during which 3 tags were disabled. This left a total of 15 tags that produced usable data, including five each from the Duroc, Yorkshire, and Landrace lines.

Next, the data were separated by date for analysis. Before moving on to the description of the parameters calculated for this study, it is important to remember that the parameters themselves were simply chosen as baseline indicators of movement or activity level. Again, the overall goal was to determine if the location data collected by the Ubisense system was accurate and could be used to monitor animals with different characteristics. A summary of the parameters calculated and recorded for each day is presented in Table 2.1, and detailed descriptions of the calculation methods follow below.

Table 2.1 Summary of key parameters calculated for each day for genetic line test and temperament test

Location Data

Parameter	Definition
Total Distance	Total distance traveled in meters when moving ≥ 0.5 m
Avg Speed When Moving	Average instantaneous speed (m/s) when moving ≥ 0.5 m
Direction Changes	# of times the animal turns, methods in Fig. 2.12 & 2.13

Event Data

Parameter	Definition
Number of Events	Number of times a tag entered the feeding/drinking zone
Total Time	Total elapsed time between each entry and exit of a zone
Avg Event Duration	Total time divided by the number of events

For each tag, the distance covered between each tag update was measured using the standard formula:

$$D = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \qquad \text{(Eq. 2)}$$

Where D is the distance (meters), X_1 and Y_1 are the initial positions, and X_2 and Y_2 are the final positions. The sum of these distances was taken to determine the total distance traveled by each pig over the course of each day. Instantaneous speed was calculated by dividing the distance traveled between each tag update by the time elapsed between updates. The instantaneous speed was used to determine each pig's average speed while moving around the pen (i.e. not lying down or sleeping). To be considered moving, the animal needed to move at least 0.5 meters between tag updates. The 0.5-meter threshold value for movement to be counted was chosen in order to avoid counting small movements of the head or shifting from side to side while lying down as intentional movements from one place in the pen to another. For the same reason, the 0.5-meter threshold for movement to be counted was also applied to the total distance.

The final objective for analysis of the tag location data was to determine the number of times each pig changed direction each day. Two methods were used to calculate the number of direction changes. In the first method, a change of direction was defined as a negative change in either the X or Y direction between tag updates ($\Delta X < 0$ m or $\Delta Y < 0$ m) coupled with a change in distance of at least 0.5 meters (Figure 2.12). The first method will be referred to as the “quadrant method” for the remainder of this paper. The issue with the quadrant method is that it assumes that the tag is moving in the positive X and positive Y direction, which is not always true. In the second method, a trigonometry-based approach was used to calculate the angular change in direction between the two previous movements after each positional update of a tag (Figure 2.13). The second method will be referred to as the “trig method” from this point forward.

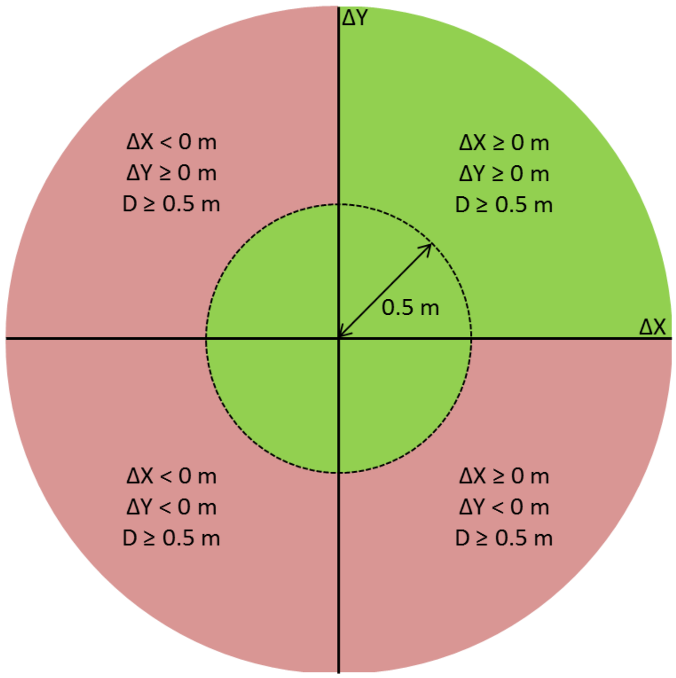

Figure 2.12 Diagram illustrating the parameters used to define a change of direction for a given animal in the genetic line test and the temperament test using the quadrant method. As a baseline, the tag must move at least 0.5 meters between tag updates. If this condition is met and the change in X or Y is negative between tag updates, a change of direction is counted.

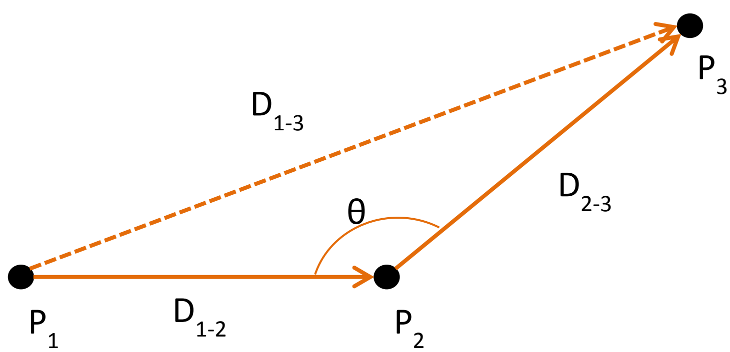

Figure 2.13 Diagram illustrating the parameters used to define a change of direction for a given animal in the genetic line test and the temperament test using the trig method. P_3 is the current position of the tag, while P_1 and P_2 are the two previous positions. $D_{1\text{-}2}$, $D_{2\text{-}3}$, and $D_{1\text{-}3}$ are the distances between those points. The angle θ was calculated using Equation 3.

The angle θ, shown in Figure 2.13, was calculated using the following equation for a triangle where all side values are known:

$$\theta = \sec\left(\frac{{D_{1-2}}^2+{D_{2-3}}^2-{D_{1-3}}^2}{2(D_{1-2})(D_{2-3})}\right) \qquad \text{(Eq. 3)}$$

In this equation, $D_{1\text{-}2}$, $D_{2\text{-}3}$, and $D_{1\text{-}3}$ are the distances between the current position (3) and the previous two positions (1 and 2) of a tag. Because the angle θ is relative to the previous movement of a tag, the trig method avoids the issue associated with the quadrant method. Direction changes were calculated by setting a threshold value for θ and a minimum distance for $D_{1\text{-}2}$ and/or $D_{2\text{-}3}$. For this experiment, direction changes were calculated using 135 degrees, 90 degrees, and 60 degrees as threshold values for θ. For each θ value, a minimum distance of 0.5 meters was first used only for $D_{2\text{-}3}$, and then for both $D_{1\text{-}2}$ and $D_{2\text{-}3}$. Setting a minimum distance for only the most recent movement ($D_{2\text{-}3}$) accounts for movements where a pig is standing still and then turns and moves away. Setting a minimum distance for both of the previous two movements requires that the pig be moving in one direction, then turn and continue moving in another. This was done to discover if the number of direction changes would stay consistent as the restrictions for what constitutes a direction change increase.

As previously mentioned, the Ubisense software is also capable of monitoring spatial interactions between tags and user-created zones within the tracking area. Each time a tag moves into or out of a zone, it triggers an event notification. However, the software does not allow the user to identify specific coordinates for the boundaries of the zones, so the boundaries must be visually approximated by placing vertices around the area of interest to create the desired zone shape. For this project, zones were created around the feeder and the drinking area. The events that occurred during each day of testing were stored in a table in the MySQL database using the same program that stored the location data.

For the analysis of the event data, each time a pig entered and then exited either the feeder or drinking area was considered one feeding or drinking event. The sum of these events was used to determine the number of times each pig visited each zone during each day. To calculate the total time spent in each zone, the elapsed time between each entrance and exit of a zone was summed over each day. Dividing the total time spent in each zone by the number of visits over the course of the day yielded the average duration of each feeding and drinking event.

2.2.5 Tracking Animals with High and Low Temperament Scores

The final objective of this project was to track pigs with high and low temperament scores. Temperament was scored on a scale from one to five, based on activity level and vocalization displayed while the pig is confined in the scale (Holl, Rohrer, & Brown-Brandl, 2010). For this test, a total of eight pigs were tagged, with four having high temperament scores (scale score = 3) and four having low temperament scores (scale score = 1). Data were then collected for nine days.

The location data for this test were imported to Excel and analyzed using identical methods to those described in the previous section for the calculation of total distance traveled, average speed, instantaneous speed, average speed while moving, and number of direction changes. Likewise, event data for this test were analyzed using the methods from the previous section for the calculation of the number of visits to each zone, total time spent in each zone, and the average duration of each feeding and drinking event (Table 2.1).

2.2.6 Statistical Analysis

Statistical analysis was carried out using SAS 9.4 (SAS Institute, Cary, NC) for the genetic line test and for the temperament test. Data were analyzed using a Proc GLM (general linear models) procedure, including an LSMEANS comparison to test for significant differences ($p<0.05$) among day, sex, and genetic line (or temperament) effects, as well as interaction effects between sex/line and sex/temperament. The SAS source code and full output for the genetic line test and temperament test can be found in Appendices B and C, respectively.

2.3 Results and Discussion

2.3.1 Stationary tag tests

To determine how tag grouping would impact system accuracy, we placed all of the tags at a known location for one hour. The average X, Y, and Z errors and the Euclidean distance for the 34 functional tags are displayed in Table 2.2. For this test, the errors in both the X and Y direction were roughly twice as large as the error in the Z direction.

Table 2.2 Average X, Y, and Z errors and average Euclidean distance for all tags during single location test

	X error	Y error	Z error	Euclidean Distance
Average	0.101	0.093	0.058	0.166
Stdev	0.086	0.080	0.050	0.105

*All table values given in meters.

To determine how well the system tracked tags throughout the pen we performed three trials of a grid test, randomizing the location of each tag in the grid for each successive trial. The average X, Y, and Z errors and the Euclidean distances for all three trials are presented in Table 2.3. We found that the average of the X and Y errors were roughly doubled in each trial when compared to the single location test. The average Z error showed the largest increase between the single location and grid test, rising between four- and five-fold in each trial.

Table 2.3 Average X, Y, and Z errors and average Euclidean distance for all tags during three grid tests

Trial 1

	X error	**Y error**	**Z error**	**Euclidean Distance**
Average	0.213	0.171	0.260	0.424
Stdev	0.288	0.167	0.431	0.509

Trial 2

	X error	**Y error**	**Z error**	**Euclidean Distance**
Average	0.182	0.147	0.197	0.346
Stdev	0.189	0.143	0.344	0.386

Trial 3

	X error	**Y error**	**Z error**	**Euclidean Distance**
Average	0.214	0.170	0.255	0.413
Stdev	0.261	0.157	0.406	0.476

*All table values in meters.

The introductory materials from the manufacturer state that accuracy of up to within 15 centimeters is possible with the Ubisense RTLS system. Results from the single location test were relatively consistent with this claim. However, results from the grid tests indicate that the system tracked tags at a higher accuracy in some locations within the pen than others. As shown above, the largest change in tracking error was in the Z direction. We also observed an increase in Euclidean distance between the single location and grid tests, which was largely a reflection of the substantial increase in Z error. During initial testing and setup in a laboratory setting, the system did not appear to have any increase in error when tracking tags in the Z direction. However, the data acquisition service had not been completed at that time, so our ability to log and analyze the data was limited. Moving the tracking system back into a laboratory setting and repeating the grid test would reveal whether the design of the swine facility or pen contributes to the Z error. The lack of variability in the Z direction in our swine pen application does not give a good estimate of Z error, which could be addressed in a lab setting. The addition of two or more sensors around the tracking area could provide a simple solution. As noted earlier, if more sensors have a clear line of sight to a tag, the calculated position will be more robust to errors.

However, the Z direction was not of significant importance for the purpose of this paper, as the head movement is not indicative of pig movement and therefore was not used. As described in the materials and methods, the mobile tag test, genetic line test, and temperament test involved collection and analysis of data in only the X and Y directions.

2.3.2 Mobile tag test

To verify that the system could track moving objects accurately, we divided the pen into a 1m × 1m grid and checked their measured positions against a series of images taken during the trial. We found that the system accurately predicted the zone a given tag was in at a rate of 84.4% (Table 2.4).

Table 2.4 Percent of observations matched by visual verification for mobile tag test

Total observations =	192
# of matches =	162
Percent matched =	84.375

During analysis of the mobile tag test data, we encountered some issues related to the programmable cameras used to photograph the X and Y axes of the pen. As shown in (Figure 2.10), the timestamp on each image includes the hour and minute, but not the second at which the image was taken. This created an issue during the visual verification of the mobile tag test data, in that we were forced to compare each image with data over the entire minute instead of at the exact second the image was captured. By looking at images from the preceding and proceeding minutes, we were able to identify observation times in which the animals were largely stationary within one zone. However, the majority of the pigs' stationary time was spent lying down in their designated resting area or at the feeder or nipple drinkers. Therefore, the majority of our observations occurred while the pigs were in one of those three areas, leaving out many areas of the pen for this test. Future work will include repeating this test with a top-down camera that can be programmed to take images at a time interval that is accurate to the second. Top-down video recordings would also solve this issue.

2.3.3 Tracking Animals from Three Genetic Lines

Statistical analysis of the genetic line test was carried out to determine differences ($p<0.05$) in total distance, average speed while moving, and number of direction changes by day, sex, line, and sex*line (Table 2.5). Results for the statistical analysis of location tracking data for the genetic line test are displayed in Table 2.6. Sex, line, and sex*line were significant effects. As shown in Table 2.6, total distance and direction changes were higher in males than in females. Likewise, total distance and direction changes were both higher in the Yorkshire line than in Duroc or Landrace. Male Landrace pigs had the highest total distance and direction changes, while female Landrace pigs had the lowest. These trends were consistent between the quadrant method and trig method for direction changes. Day was not significant for any parameter. For this project, it is preferable for day to be statistically insignificant for all parameters, because this indicates that the system is performing consistently from day to day. In the following tables, letters are used as superscripts to denote significant differences between the mean values of each parameter based on day, sex, and line or temperament. For a given parameter, mean values that have the same letter in their superscript are not significantly different.

Table 2.5 Significance (Pr>F values at the 0.05 level) by source for location tracking during the genetic line test

Source	Total Distance	Avg Moving Speed	Direction Changes (by method)					
			Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Day	0.7005	0.3528	0.7173	0.7077	0.6232	0.7201	0.7323	0.7698
Sex	0.0018	0.0693	0.0017	0.0013	0.0065	0.0329	0.0069	0.0417
Line	0.0065	0.9085	0.0201	0.0254	0.0255	0.0216	0.0341	0.0132
Sex*Line	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 2.6 LSMEANS and significance (p<0.05) by Sex, Line, and Sex*Line for location tracking during the genetic line test

Sex	Total Distance (m)	Direction Changes (by method)					
		Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Male	4504.5^{a}	2566.2^{a}	3489.1^{a}	1635.8^{a}	615.3^{a}	384.2^{a}	127.0^{a}
Female	3671.1^{b}	2049.5^{b}	2795.4^{b}	1341.9^{b}	513.2^{b}	318.0^{b}	107.5^{b}

Line	Total Distance (m)	Direction Changes (by method)					
		Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Duroc	4012.2^{a}	2252.8^{a}	3048.8^{a}	1413.1^{a}	492.3^{a}	329.6^{a}	98.7^{a}
Landrace	3632.7^{a}	2056.3^{a}	2836.5^{a}	1354.5^{a}	540.6^{a}	325.5^{a}	116.3^{ab}
Yorkshire	4618.4^{b}	2614.5^{b}	3541.5^{b}	1698.9^{b}	659.9^{b}	398.3^{b}	136.8^{b}

Sex	Line	Total Distance (m)	Avg Moving Speed (m/s)	Direction Changes (by method)					
				Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Male	Duroc	3948.8^{acd}	0.416^{abcde}	2152.2^{acd}	2911.9^{acd}	1292.4^{ad}	433.7^{ade}	297.6^{ad}	83.7^{ade}
Male	Landrace	5138.1^{bcf}	0.429^{abdf}	2969.7^{bcf}	4106.5^{bcf}	1951.8^{bcf}	754.2^{bcf}	467.7^{bf}	162.6^{bcf}
Male	Yorkshire	4426.4^{abcdf}	0.398^{ace}	2576.6^{abcdf}	3449^{abcdf}	1663^{bcdf}	658^{bcdf}	387.4^{cdf}	134.8^{bcdf}
Female	Duroc	4075.6^{acd}	0.425^{abdf}	2353.3^{acdf}	3185.7^{acdf}	1533.7^{acdf}	550.8^{acdf}	361.6^{acdf}	113.7^{acdf}
Female	Landrace	2127.3^{e}	0.405^{ace}	1142.8^{e}	1566.5^{e}	757.2^{e}	327^{ae}	183.2^{e}	70^{ae}
Female	Yorkshire	4810.3^{bcf}	0.441^{bf}	2652.4^{bcdf}	3633.9^{bcdf}	1734.8^{bcdf}	661.8^{bcdf}	409.2^{bcdf}	138.8^{bcdf}

Statistical analysis of the genetic line test was carried out to determine differences ($p<0.05$) in number of feeding events, total time, and average event duration by day, sex, line, and sex*line (Table 2.7). Results for the statistical analysis of feeder event data for the genetic line test are displayed in Table 2.8. Line was significant for number of feeding events, while sex*line was significant for number of feeding events and average duration. Yorkshire pigs had a higher average number of feeding events than both Duroc and Landrace. The average durations of feeding events for male Duroc and female Landrace pigs were significantly higher than all other sex* line groups. Day and Sex were not significant for any parameter.

Table 2.7 Significance (Pr>F values at the 0.05 level) by source for feeding events during the genetic line test

Source	# of Feed Events	Total Time	Avg Duration
Day	0.2483	0.5903	0.4749
Sex	0.7445	0.7567	0.8843
Line	0.0043	0.1111	0.2553
Sex*Line	0.0001	0.7662	0.0001

Table 2.8 LSMEANS and significance (p<0.05) by Line and Sex*Line for feeding events during the genetic line test

Line	# of Feed Events
Duroc	172.5[a]
Landrace	135.8[a]
Yorkshire	243.5[b]

Sex	Line	# of Feed Events	Avg Duration (s)
Male	Duroc	111.1[ae]	70.8[a]
Male	Landrace	190.5[bdf]	15.8[b]
Male	Yorkshire	279.1[cdf]	15.2[b]
Female	Duroc	233.9[bcdf]	14.2[b]
Female	Landrace	81.1[ae]	74.1[a]
Female	Yorkshire	207.8[bcdf]	24[b]

Statistical analysis of the genetic line test was carried out to determine differences ($p<0.05$) in number of drinking events, total time, and average event duration by day, sex, line, and sex*line (Table 2.9). Results for the statistical analysis of drinking event data for the genetic line test are displayed in Table 2.10. Sex was significant for number of drinking events and total time, while sex*line was significant for total time and average duration. Number of drinking events and the total drinking time were higher in males than females. Male Duroc pigs had the highest mean total drinking time, while female Landrace pigs had the highest drinking event duration among all sex*line groups. Day and line were not significant for any parameter.

Table 2.9 Significance (Pr>F values at the 0.05 level) by source for drinking events during the genetic line test

Source	# of Water Events	Total Time	Avg Duration
Day	0.8598	0.6053	0.5442
Sex	0.0005	0.0204	0.0557
Line	0.1563	0.432	0.2066
Sex*Line	0.427	0.0155	0.0411

Table 2.10 LSMEANS and significance (p<0.05) by Sex and Sex*Line for drinking events during the genetic line test

Sex	# of Water Events	Total Time (s)
Male	173.1^{a}	3338.3^{a}
Female	96.8^{b}	2225.1^{b}

Sex	Line	Total Time (s)	Avg Duration (s)
Male	Duroc	4514.2^{ac}	28.3^{a}
Male	Landrace	2345^{bcdef}	13.6^{a}
Male	Yorkshire	3155.8^{abcef}	17^{a}
Female	Duroc	1642^{bdef}	31.4^{a}
Female	Landrace	2510.3^{bcdef}	68^{b}
Female	Yorkshire	2523^{bcdef}	20.7^{a}

2.3.4 Tracking Animals with High and Low Temperament Scores

Statistical analysis of the temperament test was carried out to determine differences (p<0.05) in total distance, average speed while moving, and number of direction changes by day, sex, temperament, and sex*temperament (Table 2.11). Results for the statistical analysis of location tracking data for the temperament test are displayed in Table 2.12. Sex was a significant effect for total distance and direction changes. Males showed significantly higher daily total distance and direction changes than females. This effect was consistent for both the quadrant method and trig method of measuring direction changes. Day, temperament, and sex*temperament were not significant for any parameter.

Table 2.11 Significance (Pr>F values at the 0.05 level) by source for location tracking during the temperament test

Source	Total Distance	Avg Moving Speed	Direction Changes (by method)					
			Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Day	0.1865	0.844	0.0971	0.1468	0.0934	0.2879	0.1532	0.4551
Sex	<.0001	0.3712	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Temperament	0.9943	0.5058	0.2216	0.6114	0.1382	0.1361	0.1435	0.1643
Sex*Temperament	0.866	0.7973	0.3583	0.6022	0.2118	0.139	0.1606	0.093

Table 2.12 LSMEANS and significance (p<0.05) by Sex for location tracking during the temperament test

Sex	Total Distance (m)	Direction Changes (by method)					
		Quadrant	*θ<135, D2-3>0.5m*	*θ<90, D2-3>0.5m*	*θ<90, D1-3 and D2-3>0.5m*	*θ<60, D2-3>0.5m*	*θ<60, D1-3 and D2-3>0.5m*
Male	5118.1^{a}	2889.0^{a}	3842.8^{a}	1751.7^{a}	679.3^{a}	404.0^{a}	141.2^{a}
Female	3195.8^{b}	1779.7^{b}	2419.0^{b}	1168.2^{b}	460.6^{b}	273.4^{b}	96.0^{b}

Statistical analysis of the temperament test was carried out to determine differences ($p<0.05$) in number of feeding events, total time, and average event duration by day, sex, temperament, and sex*temperament (Table 2.13). Results for the statistical analysis of feeder event data for the temperament test are displayed in Table 2.14. Sex, temperament, and sex*temperament were significant effects for the number of feeding events. Temperament was also significant for the total feeding time. Males nearly doubled the average number of feeding events compared to females. Unexpectedly, low (1) temperament animals had a significantly larger number of feeding events and higher total feeding time than high (3) temperament animals. Male low temperament pigs had the highest number of feeding events among all sex*temperament groups. Day was not significant for any parameter.

Table 2.13 Significance (Pr>F values at the 0.05 level) by source for feeding events during the temperament test

Source	# of Feed Events	Total Time	Avg Duration
Day	0.0779	0.3815	0.536
Sex	<.0001	0.0735	0.2303
Temperament	<.0001	0.0096	0.2915
Sex*Temperament	0.0212	0.8396	0.5677

Table 2.14 LSMEANS and significance ($p<0.05$) by Sex, Temperament, and Sex*Temperament for feeding events during the temperament test

Sex	# of Feed Events
Male	456.7[a]
Female	268.5[b]

Temperament	# of Feed Events	Total Time (s)
1	459.5[a]	8957.0[a]
3	265.6[b]	6149.5[b]

Sex	Temperament	# of Feed Events
Male	1	599.5[a]
Male	3	313.9[bc]
Female	1	319.7[bc]
Female	3	217.3[b]

Statistical analysis of the temperament test was carried out to determine differences ($p<0.05$) in number of drinking events, total time, and average event duration by day, sex, temperament, and sex*temperament (Table 2.15). Results for the statistical analysis of drinking event data for the temperament test are displayed in Table 2.16. Sex was a significant effect for the number of drinking events and the average duration, while temperament was significant only for the average duration. The number of drinking events was nearly double in males compared to females. Interestingly, the average duration of drinking events was significantly higher in females than in males. Possible causes for this effect are discussed below. Day and sex*temperament were not significant for any parameter.

Table 2.15 Significance (Pr>F values at the 0.05 level) by source for drinking events during the temperament test

Source	# of Water Events	Total Time	Avg Duration
Day	0.1892	0.1391	0.4785
Sex	<.0001	0.1252	0.0003
Temperament	0.5784	0.1866	0.0357
Sex*Temperament	0.176	0.3332	0.6726

Table 2.16 LSMEANS and significance (p<0.05) by Sex and Temperament for temperament test drinking events

Sex	# of Water Events	Avg Duration (s)
Male	62.4[a]	14.5[a]
Female	32[b]	24[b]

Temperament	Avg Duration (s)
1	21.5[a]
3	17[b]

Based on the results of our statistical analyses presented in Tables 2.5-2.10, we can conclude that it is possible to detect some differences in swine activity and space utilization between animals with different genetic lineage and temperament scores through location tracking with the active RFID tracking system. It is worth noting, however, that total number of events and the average event duration for the feeding and drinking event data is likely not an accurate representation of the true number of visits to either zone or the average duration of an event in either zone. It is very likely that the tags pass into and out of a zone multiple times during an actual visit to the feeder or nipple drinker. For example, an animal may be standing near the edge of the established feeder zone, and even slight movements of the head would generate repeated entry and exit events. Likewise, simply walking past the feeder or nipple drinker may generate one or more entry and exit events. The overall effect of these false events is to drive up the total number of feeder or drinker events, resulting in a decrease in average event time. This may also explain why low temperament animals would have a higher number of feeding or drinking events, as seen in Table 2.14 and Table 2.16. A pig with a low temperament may get pushed out of the feeding or drinking zone, and any subsequent re-entries would trigger extra feeding or drinking events. This effect could be mitigated by importing the data to MATLAB or a similar program, which would give greater control over the establishment of zone boundaries than is possible within the Ubisense software.

2.4 Data Jumps

Discussion of some of the future work needed to address system issues is presented in the previous section, but there is one further point that should be addressed as we look toward taking the next steps. Dr. Matti Pastell from the Natural Resources Institute Finland (Luke) is also working with the Ubisense active RFID system. Through Dr. Pastell, we learned that the Ubisense system has shown a tendency to create large jumps in the location data (personal communication with Dr. Pastell, June 28, 2016).

Analysis indicates that our data has a similar issue. An example of a large jump in the data is presented in Figure 2.14. The jump in the data can be seen in the middle of the plot, where the tag does not update positions for 17 seconds. When it reappears, it has moved nearly 4 meters in the X direction. In the following tag updates, the X position settles back around the original location. Similarly, jumps can be seen in the Y values, but were not as large during this sampling window.

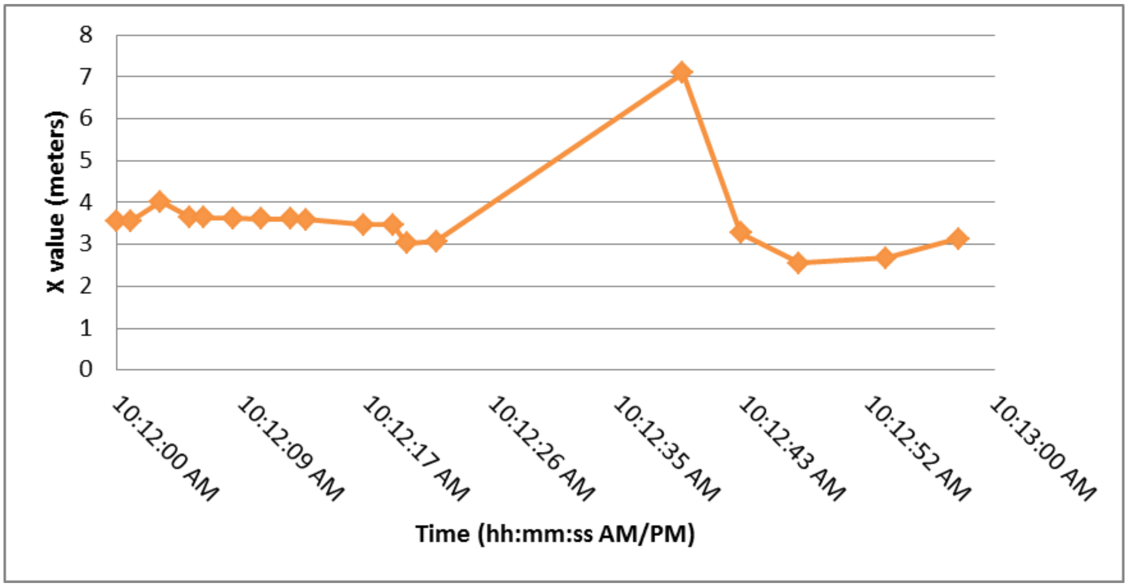

Figure 2.14 Plotting X values for a single tag over one minute during the genetic line test. The jump in the data can be seen in the middle of the plot, where the tag disappears for 17 seconds and then reappears 4 meters away before settling back to the previously measured location.

For the purpose of this thesis, we wanted to further characterize these jumps to determine if filtering them out is possible or necessary. First, we wanted to know how often data jumps occur and if they occur more frequently in specific tags. To do so, we needed to identify the conditions for a movement that would make us suspect a jump in the data had occurred. Figure 2.15 shows how often certain time intervals (Δt) occur between tag updates during a given day. The vast majority of the time, only 1-2 seconds elapsed between tag updates. Therefore, we chose to focus on movements of 3 meters or greater, as it seems at least unlikely that a pig would move that far in under 2 seconds.

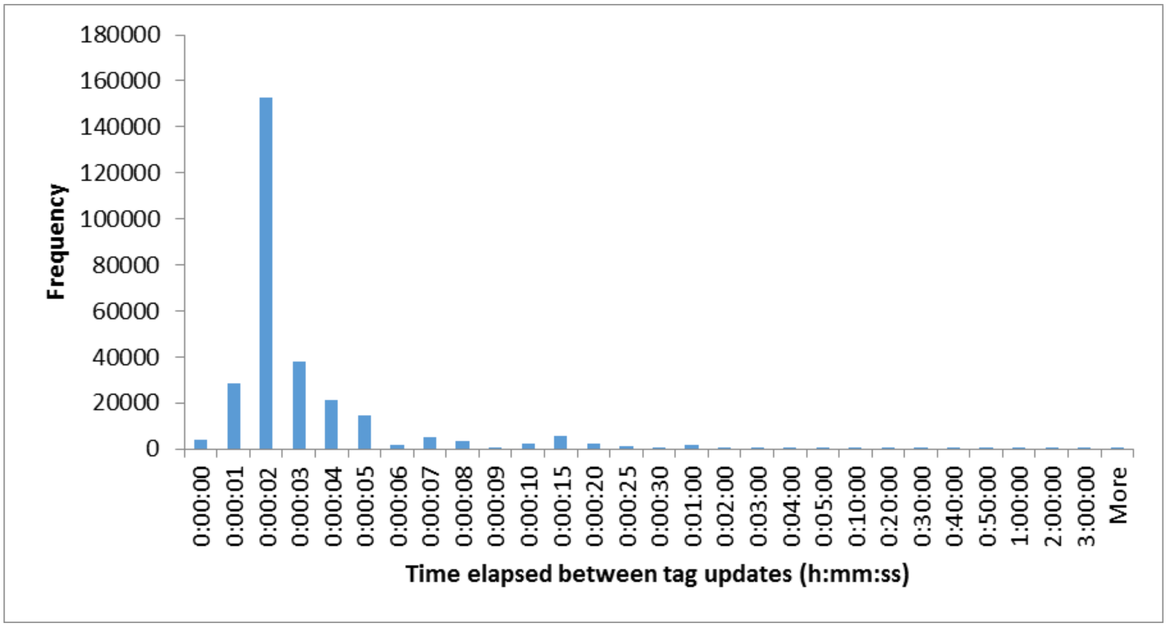

Figure 2.15 Frequency distribution showing the number of times in a given day that each time interval occurs between tag positional updates.

For both the genetic line test and the temperament test, we extracted all of the movements of 3 meters or greater and sorted them into tables by tag and by day (Figure 2.16 and Figure 2.17). As shown in Figures 2.16 and 2.17, the daily percentage of movements that were 3 meters or greater was around 0.3% for both tests. This indicates that the data jumps, at least those of this magnitude, do not occur very frequently. Additionally, there does not appear to be any individual tag that consistently measures more movements of 3 meters or greater than the other tags. In many cases, the number of movements of 3 meters or greater varies by nearly double from day to day for a single tag. Figure 2.18 shows the frequency distribution for the daily number of movements of 3 meters or greater for both the genetic line test and the temperament test. The spike at the zero level for the temperament test distribution is due to days where certain tags were disabled and did not generate data. Excluding that spike, the histograms for both tests show relatively normal distributions for the daily number of movements of 3 meters or greater. Taken together, these results indicate that the data jump issue is related to the system as a whole, and affects each tag with random frequency.

Tag#	Day 1	Day 2	Day 3	Day 4	Day 5	Average
tag03	95	43	62	63	33	59.2
tag19	48	33	56	43	49	45.8
tag20	20	37	38	53	37	37
tag21	102	57	106	45	55	73
tag22	40	51	44	47	41	44.6
tag23	35	54	36	26	34	37
tag24	29	41	31	49	54	40.8
tag25	60	61	72	76	47	63.2
tag26	58	26	18	11	27	28
tag27	33	84	76	30	52	55
tag28	62	52	68	53	50	57
tag29	48	49	38	37	66	47.6
tag30	51	28	15	26	26	29.2
tag31	88	66	47	66	51	63.6
tag32	34	19	39	65	79	47.2
Total	803	701	746	690	701	728.2
# of Daily Updates	304561	286281	291657	308000	285174	295135
% of moves >3m	0.26%	0.24%	0.26%	0.22%	0.25%	0.25%

Figure 2.16 For the genetic line test, how many times per day each tag makes a movement of greater than 3m between tag updates, and the daily percentage of movements that were >3m.

Tag#	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Average
tag19	64	30	40	57	70	43	53	40	n/a	49.6
tag20	53	63	58	55	41	43	66	42	64	53.9
tag21/33	36	15	n/a	n/a	n/a	20	46	23	45	30.8
tag23	29	19	35	45	43	69	80	43	69	48.0
tag26/34	66	61	45	n/a	n/a	43	61	96	49	60.1
tag29	71	84	65	82	59	63	24	n/a	n/a	64.0
tag30	76	36	34	62	56	121	54	92	93	69.3
tag32	111	117	88	107	95	118	92	73	87	98.7
Total	506	425	365	408	364	520	476	409	407	431.1
# of Daily Updates	167726	150197	130478	106055	124740	120093	104573	97819	87832	121057.0
% of moves >3m	0.30%	0.28%	0.28%	0.38%	0.29%	0.43%	0.46%	0.42%	0.46%	0.36%

Figure 2.17 For the temperament test, how many times per day each tag makes a movement of greater than 3m between tag updates, and the daily percentage of movements that were >3m. Data labeled n/a refers to days where a tag was disabled and had to be replaced.

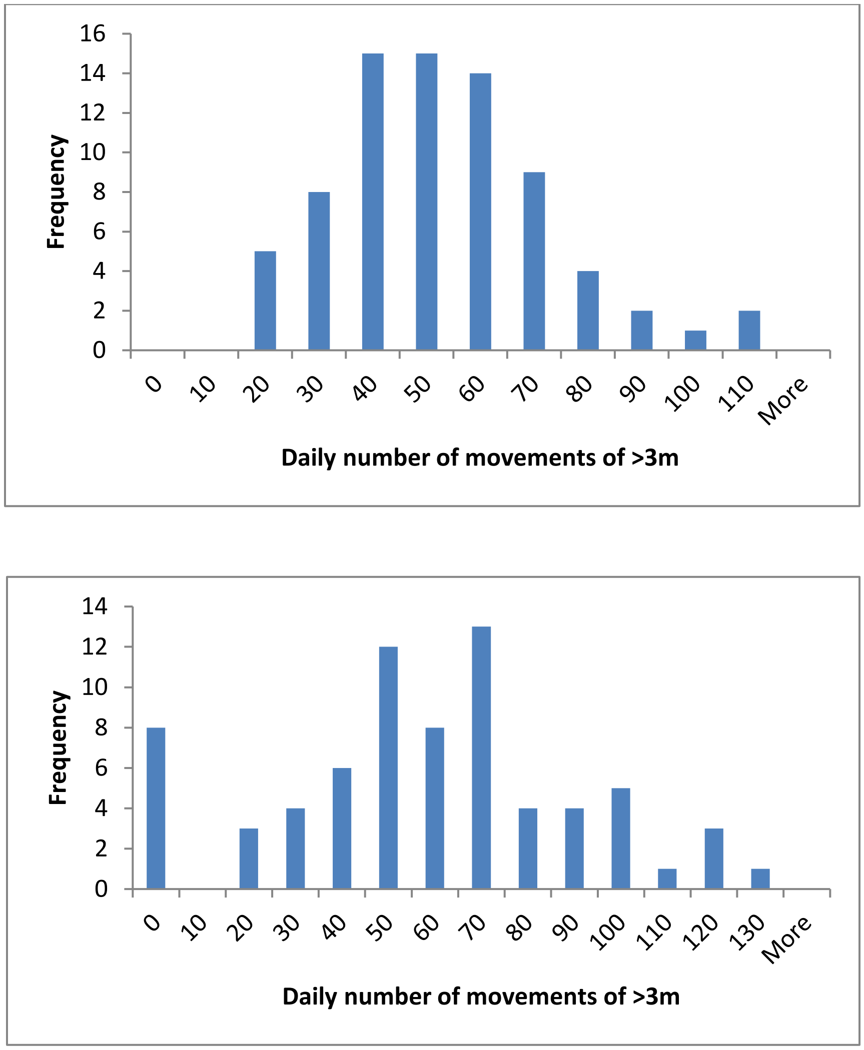

Figure 2.18 Histograms showing the frequency distributions for the daily number of movements of 3m or great for both the genetic line test (Top) and the temperament test (bottom). The spike at the zero level is due to days where certain tags were disabled and did not generate data.

Finally, we wanted to compare the tag movements of 3 meters or greater with the entire set of tag movements throughout the day. This was done in order to see if the large jumps occurred primarily in either the X or Y direction, and if their movement pattern matched that of normal movements throughout the day. We extracted all of the movements of 3 meters or greater for a full day and calculated the percentage of each movement that occurred in the X and Y directions, then performed the same analysis on all of the movements from the entire day. Figure 2.19 shows the distributions in the X and Y directions for each analysis. The distributions in the X and Y direction are consistent between the data for movements larger than 3 meters and the data for the entire day, indicating that movement pattern is similar regardless of the distance travelled between tag updates.

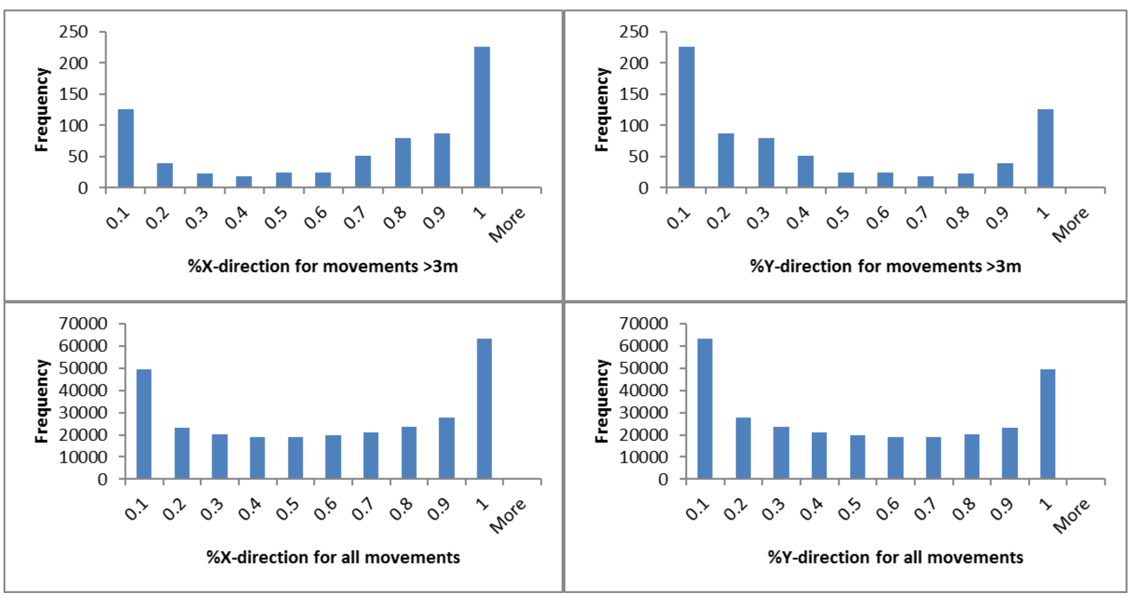

Figure 2.19 Frequency distribution for %X-direction (top-left) and %Y-direction (top-right) of movements >3m during a full day, and %X-direction (bottom-left) and %Y-direction (bottom-right) for all movements during a full day.

Overall, our analysis suggests that the data jumps affect the entire population of tags, and that the occurrence of these jumps is random. Additionally, movements of greater than 3 meters between tag updates only occur around 0.3% of the time. These results lead us to believe that in its current form, the Ubisense system would be best suited for monitoring hourly or daily movement data, in which a level of certainty can be assumed. If the desired use of the system is to take instantaneous measurements, a method of filtering out the random data jumps will be needed.

2.5 Conclusions

This study was conducted to determine whether an active RFID tracking system could be applied in a swine pen to reliably monitor animal activity and space utilization. Recent research in precision livestock farming, including the work presented here, has focused primarily on establishing and evaluating sensor-based data collection techniques on livestock operations. With an accuracy of 84.4%, the results of our initial evaluation of the active RFID system are consistent with other work in the field of PLF. Top-down image processing techniques have been used in swine research to automatically determine individual animal identity with 88.7% accuracy (Kashiha *et al.*, 2013). Kashiha *et al*. were able to use the information to track each individual's appearances in the feeding, drinking, resting, and defecating zones within the pen. Aggressive interactions between finishing pigs in confinement have also been analyzed using top-down video recordings (Oczak *et al.*, 2013 and Viazzi, 2014). Oczak *et al* used a human observer to manually label the phases of aggressive interactions with the goal of the eventual creation of a program that could recognize these interactions. Viazzi continued this work, using image analysis techniques to detect aggressive interactions with 89.0% accuracy. The primary advantage of the active RFID system is that once it is properly calibrated, the data do not need post processing by image or video analysis. The data is stored in a simple format that could be directly fed into a decision making model.

We found that grouping the tags at a single location did not produce any interference that affected the ability of the system to locate tags in the pen (Table 2.1). However, placing the tags in a grid across the pen resulted in a higher average location error, particularly in the Z direction, indicating that there are areas in the pen where the tags track more accurately than others (Table 2.2). The more sensors that receive a signal, the more robust they are to this error.

The active RFID system provides a new stream of location data that can be applied to behavioral research of pigs in confinement. Initial testing of the system was performed with animals from different genetic lines and animals with high and low temperament scores. Statistical analysis of this data suggests that there are differences ($p<0.05$) in animal activity, primarily in total distance traveled and time spent feeding or drinking, based on genetic and temperament factors.

In conclusion, this study shows that an active RFID tracking system is capable of providing accurate location data in a finishing swine pen. The data generated could be used to map feeding behaviors, drinking behaviors, access to cooling systems, and animal interactions. Most importantly, the system could be combined with other biological sensors to provide more complete individual animal health profiles. As detailed in the previous section, the system is prone to generate large data jumps. The work presented here shows that this effect is random and affects all of the tags, meaning that instantaneous measurements cannot necessarily be trusted. Without a reliable data filtering method, the data should only be used to calculate average values over several hours or days. Therefore, future work into development of a filtering method for the data jumps would be highly beneficial to the overall capabilities of the active RFID tracking system.

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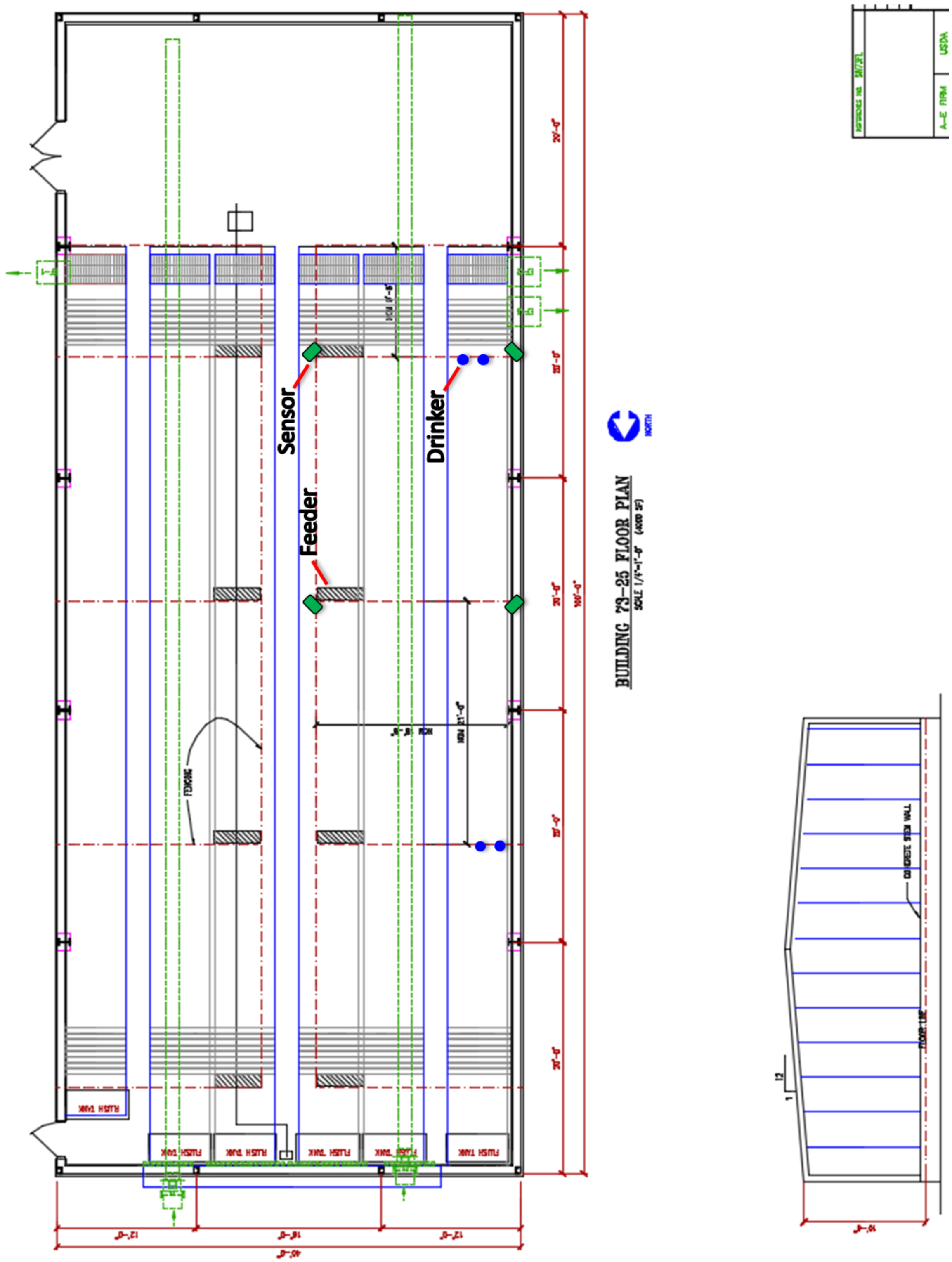
APPENDIX A

DIAGRAM OF SWINE BUILDING, SWINE PEN AND KEY ELEMENTS


Sensor
Feeder
Drinker
FENCING
FLUSH TANK
NORTH
BUILDING 73-25 FLOOR PLAN
CONCRETE STEM WALL
FLOOR LINE
USDA
A-E FIRM

APPENDIX B

SAMPLE OF SAS SOURCE CODE AND OUTPUT FOR GENETIC LINE TEST

This a sample of one SAS output, only including significant effects, for the Genetic Line Test. Full SAS outputs are located in the supplemental electronic materials.

Source Code:

```
Proc GLM;
class Day Sex Line;
model Total_Dist Avg_Moving_Speed Dir_Change = Day Sex Line Sex*Line;
lsmeans Sex Line Sex*Line /stderr pdiff;
run;
```

The GLM Procedure

The SAS System

Class Level Information

Class	Levels	Values
Day	5	06APR2016 07APR2016 08APR2016 09APR2016 10APR2016
Sex	2	1 2
Line	3	Duroc Landrace Yorkshire

Number of Observations Read	75
Number of Observations Used	75

The SAS System

The GLM Procedure

Dependent Variable: Total_Dist Total_Dist

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	65192493.5	7243610.4	7.69	<.0001
Error	65	61264886.3	942536.7		
Corrected Total	74	126457379.8			

R-Square	Coeff Var	Root MSE	Total_Dist Mean
0.515529	23.08704	970.8433	4205.144

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	4	2069215.52	517303.88	0.55	0.7005
Sex	1	9972603.55	9972603.55	10.58	0.0018
Line	2	10281082.20	5140541.10	5.45	0.0065
Sex*Line	2	42869592.22	21434796.11	22.74	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	4	2069215.52	517303.88	0.55	0.7005
Sex	1	12501318.13	12501318.13	13.26	0.0005
Line	2	11864481.55	5932240.78	6.29	0.0032
Sex*Line	2	42869592.22	21434796.11	22.74	<.0001

The SAS System

The GLM Procedure

Dependent Variable: Avg_Moving_Speed Avg_Moving_Speed

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	0.01731814	0.00192424	3.82	0.0007
Error	65	0.03278211	0.00050434		
Corrected Total	74	0.05010025			

R-Square	Coeff Var	Root MSE	Avg_Moving_Speed Mean
0.345670	5.321777	0.022458	0.421993

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	4	0.00226808	0.00056702	1.12	0.3528
Sex	1	0.00172025	0.00172025	3.41	0.0693
Line	2	0.00009691	0.00004845	0.10	0.9085
Sex*Line	2	0.01323290	0.00661645	13.12	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	4	0.00226808	0.00056702	1.12	0.3528
Sex	1	0.00156544	0.00156544	3.10	0.0828
Line	2	0.00017972	0.00008986	0.18	0.8372
Sex*Line	2	0.01323290	0.00661645	13.12	<.0001

The SAS System

The GLM Procedure

Dependent Variable: Dir_Change Dir_Change

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	23333890.43	2592654.49	6.97	<.0001
Error	65	24168453.52	371822.36		
Corrected Total	74	47502343.95			

R-Square	Coeff Var	Root MSE	Dir_Change Mean
0.491216	25.64252	609.7724	2377.973

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	4	781641.95	195410.49	0.53	0.7173
Sex	1	3966689.88	3966689.88	10.67	0.0017
Line	2	3087244.63	1543622.32	4.15	0.0201
Sex*Line	2	15498313.97	7749156.99	20.84	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	4	781641.95	195410.49	0.53	0.7173
Sex	1	4805000.00	4805000.00	12.92	0.0006
Line	2	3848701.67	1924350.84	5.18	0.0082
Sex*Line	2	15498313.97	7749156.99	20.84	<.0001

The SAS System

The GLM Procedure
Least Squares Means

Sex	Total_Dist LSMEAN	Standard Error	H0:LSMEAN=0 Pr > |t|	H0:LSMean1=LSMean2 Pr > |t|
1	4504.44919	167.11377	<.0001	0.0005
2	3671.07192	156.32062	<.0001	

Sex	Avg_Moving_Speed LSMEAN	Standard Error	H0:LSMEAN=0 Pr > |t|	H0:LSMean1=LSMean2 Pr > |t|
1	0.41481697	0.00386567	<.0001	0.0828
2	0.42414270	0.00361600	<.0001	

Sex	Dir_Change LSMEAN	Standard Error	H0:LSMEAN=0 Pr > |t|	H0:LSMean1=LSMean2 Pr > |t|
1	2566.17778	104.96170	<.0001	0.0006
2	2049.51111	98.18268	<.0001	

Line	Total_Dist LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
Duroc	4012.23052	198.17256	<.0001	1
Landrace	3632.67863	198.17256	<.0001	2
Yorkshire	4618.37252	198.17256	<.0001	3

Least Squares Means for effect Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Total_Dist

i/j	1	2	3
1		0.1803	0.0342
2	0.1803		0.0008
3	0.0342	0.0008	

Line	Avg_Moving_Speed LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
Duroc	0.42114165	0.00458412	<.0001	1
Landrace	0.41735549	0.00458412	<.0001	2
Yorkshire	0.41994236	0.00458412	<.0001	3

Least Squares Means for effect Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Avg_Moving_Speed

i/j	1	2	3
1		0.5612	0.8538
2	0.5612		0.6912
3	0.8538	0.6912	

Line	Dir_Change LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
Duroc	2252.76667	124.46927	<.0001	1
Landrace	2056.26667	124.46927	<.0001	2
Yorkshire	2614.50000	124.46927	<.0001	3

Least Squares Means for effect Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Dir_Change

i/j	1	2	3
1		0.2684	0.0439
2	0.2684		0.0023
3	0.0439	0.0023	

Sex	Line	Total_Dist LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
1	Duroc	3948.84446	307.00761	<.0001	1
1	Landrace	5138.08755	250.67066	<.0001	2
1	Yorkshire	4426.41557	307.00761	<.0001	3
2	Duroc	4075.61658	250.67066	<.0001	4
2	Landrace	2127.26972	307.00761	<.0001	5
2	Yorkshire	4810.32947	250.67066	<.0001	6

Least Squares Means for effect Sex*Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Total_Dist

i/j	1	2	3	4	5	6
1		0.0038	0.2754	0.7501	<.0001	0.0334
2	0.0038		0.0772	0.0039	<.0001	0.3586
3	0.2754	0.0772		0.3794	<.0001	0.3363
4	0.7501	0.0039	0.3794		<.0001	0.0422
5	<.0001	<.0001	<.0001	<.0001		<.0001
6	0.0334	0.3586	0.3363	0.0422	<.0001	

Sex	Line	Avg_Moving_Speed LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
1	Duroc	0.41665226	0.00710169	<.0001	1
1	Landrace	0.42920899	0.00579851	<.0001	2
1	Yorkshire	0.39858967	0.00710169	<.0001	3
2	Duroc	0.42563104	0.00579851	<.0001	4
2	Landrace	0.40550199	0.00710169	<.0001	5
2	Yorkshire	0.44129506	0.00579851	<.0001	6

Least Squares Means for effect Sex*Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Avg_Moving_Speed

i/j	1	2	3	4	5	6
1		0.1755	0.0767	0.3310	0.2710	0.0091
2	0.1755		0.0014	0.6641	0.0120	0.1453
3	0.0767	0.0014		0.0044	0.4937	<.0001
4	0.3310	0.6641	0.0044		0.0317	0.0605
5	0.2710	0.0120	0.4937	0.0317		0.0002
6	0.0091	0.1453	<.0001	0.0605	0.0002	

Sex	Line	Dir_Change LSMEAN	Standard Error	Pr > |t|	LSMEAN Number
1	**Duroc**	2152.20000	192.82696	<.0001	1
1	**Landrace**	2969.73333	157.44255	<.0001	2
1	**Yorkshire**	2576.60000	192.82696	<.0001	3
2	**Duroc**	2353.33333	157.44255	<.0001	4
2	**Landrace**	1142.80000	192.82696	<.0001	5
2	**Yorkshire**	2652.40000	157.44255	<.0001	6

Least Squares Means for effect Sex*Line
Pr > |t| for H0: LSMean(i)=LSMean(j)
Dependent Variable: Dir_Change

i/j	1	2	3	4	5	6
1		0.0017	0.1245	0.4221	0.0004	0.0487
2	0.0017		0.1191	0.0073	<.0001	0.1589
3	0.1245	0.1191		0.3731	<.0001	0.7617
4	0.4221	0.0073	0.3731		<.0001	0.1839
5	0.0004	<.0001	<.0001	<.0001		<.0001
6	0.0487	0.1589	0.7617	0.1839	<.0001	

APPENDIX C

SAMPLE OF SAS SOURCE CODE AND OUTPUT FOR TEMPERAMENT TEST

This a sample of one SAS output, only including significant effects, for the Temperament Test. Full SAS outputs are located in the supplemental electronic materials.

Source Code:

```
Proc GLM;
class Day Sex Temperament;
model Total_Dist Avg_Moving_Speed Dir_Change = Day Sex Temperament
Sex*Temperament;
lsmeans Day Sex Temperament Sex*Temperament /stderr pdiff;
run;
```

The SAS System

The GLM Procedure

Class Level Information

Class	Levels	Values
Day	9	15APR2016 16APR2016 17APR2016 18APR2016 19APR2016 20APR2016 21APR2016 22APR2016 23APR2016
Sex	2	1 2
Temperament	2	1 3

Number of Observations Read	72
Number of Observations Used	62

The SAS System

The GLM Procedure

Dependent Variable: Total_Dist Total_Dist

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	67553944.5	6141267.7	5.19	<.0001
Error	50	59184373.1	1183687.5		
Corrected Total	61	126738317.6			

R-Square	Coeff Var	Root MSE	Total_Dist Mean
0.533019	27.52662	1087.974	3952.444

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	8	14062068.83	1757758.60	1.48	0.1865
Sex	1	53457750.14	53457750.14	45.16	<.0001
Temperament	1	61.07	61.07	0.00	0.9943
Sex*Temperament	1	34064.47	34064.47	0.03	0.8660

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	8	15121447.53	1890180.94	1.60	0.1496
Sex	1	51571295.08	51571295.08	43.57	<.0001
Temperament	1	2902.70	2902.70	0.00	0.9607
Sex*Temperament	1	34064.47	34064.47	0.03	0.8660

The SAS System

The GLM Procedure

Dependent Variable: Avg_Moving_Speed Avg_Moving_Speed

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	0.00314665	0.00028606	0.49	0.9000
Error	50	0.02913037	0.00058261		
Corrected Total	61	0.03227702			

R-Square	Coeff Var	Root MSE	Avg_Moving_Speed Mean
0.097489	5.604897	0.024137	0.430646

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	8	0.00237168	0.00029646	0.51	0.8440
Sex	1	0.00047437	0.00047437	0.81	0.3712
Temperament	1	0.00026176	0.00026176	0.45	0.5058
Sex*Temperament	1	0.00003883	0.00003883	0.07	0.7973

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	8	0.00243248	0.00030406	0.52	0.8344
Sex	1	0.00061353	0.00061353	1.05	0.3097
Temperament	1	0.00029670	0.00029670	0.51	0.4788
Sex*Temperament	1	0.00003883	0.00003883	0.07	0.7973

The SAS System

The GLM Procedure

Dependent Variable: Dir_Change Dir_Change

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	25717559.99	2337960.00	6.42	<.0001
Error	50	18198979.70	363979.59		
Corrected Total	61	43916539.69			

R-Square	Coeff Var	Root MSE	Dir_Change Mean
0.585601	26.97979	603.3072	2236.145

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Day	8	5271635.58	658954.45	1.81	0.0971
Sex	1	19575373.66	19575373.66	53.78	<.0001
Temperament	1	557721.69	557721.69	1.53	0.2216
Sex*Temperament	1	312829.06	312829.06	0.86	0.3583

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Day	8	5869808.92	733726.12	2.02	0.0635
Sex	1	17173090.64	17173090.64	47.18	<.0001
Temperament	1	745216.16	745216.16	2.05	0.1587
Sex*Temperament	1	312829.06	312829.06	0.86	0.3583

The SAS System

Sex	Total_Dist LSMEAN	Standard Error	H0:LSMEAN=0 Pr > |t|	H0:LSMean1=LSMean2 Pr > |t|
1	5118.08290	230.27932	<.0001	<.0001
2	3195.76963	178.63999	<.0001	

Sex	Dir_Change LSMEAN	Standard Error	H0:LSMEAN=0 Pr > |t|	H0:LSMean1=LSMean2 Pr > |t|
1	2889.03767	127.69530	<.0001	<.0001
2	1779.74951	99.06008	<.0001	