PigNet: Failure-Tolerant Pig Activity Monitoring System Using Structural Vibration

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ABSTRACT

Automated monitoring of livestock behavior can help farmers economically by detecting changes in animal welfare. Prior approaches use video, which requires light and high storage capability, or motion detection, which has difficulty separating subtle activities. Wearable sensors can address these issues but are vulnerable to destruction by the animals. To the best of our knowledge, we present the first system that uses structural vibration to track animal behavior, and the first system to automatically detect piglet nursing. *PigNet* uses vibration sensors attached to a pig pen to sense the unique vibration patterns and changes in structural response caused by the animals' movement and position within the pen. Combined with our knowledge of pig behavior, we use this physical knowledge of vibration characteristics to detect pig activities and track piglet growth in a real farm environment. Our system is designed to be robust to the harsh environment, which can create unpredictable noise, as well as physically damage or disconnect sensor nodes. When deployed in a real-world farm environment, our system was able to achieve a daily pen-level status profile of up to 90% accuracy, which tracks nursing activity, sow lying activity, and changes in piglet growth over the weeks-long pre-weaning period.

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CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Applied computing → Agriculture**.

KEYWORDS

smart farming, structural vibration sensing, ubiquitous sensing, activity detection

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1 INTRODUCTION

Pork is one of the most popular meat products in the world, encompassing 36% of all meat consumption in 2014. In 2019, 120 million tons of pork were consumed worldwide [2]. Pig farming is a huge industry worldwide, and there is a vested interest in monitoring the growth and health of pigs. In pig production, farrowing mortality, pre-weaning mortality and quality of the piglets are major economic factors for farm owners. Implementing automatic monitoring throughout the high-risk farrowing and pre-weaning periods could help farmers to reduce risk and better protect their livestock.

Prior work takes a number of approaches, using video or image analysis, motion detection, or wearable sensors on the pigs [19,

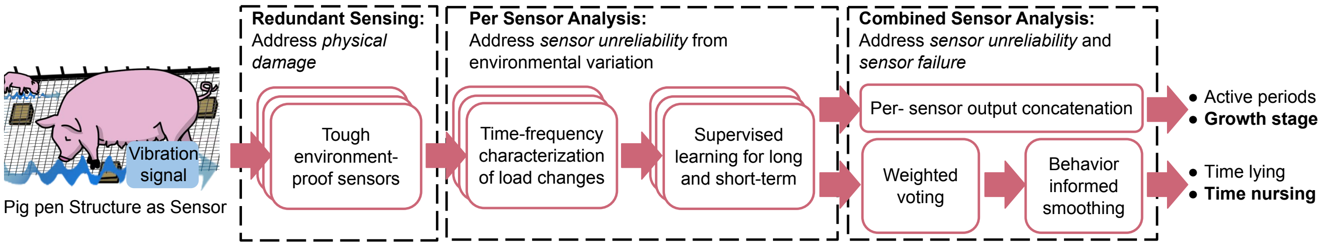

Figure 1: *PigNet* System Overview

31, 48, 57, 71]. However, these approaches bring severe drawbacks. Image based approaches require constant light and large processing and storage capability, making their deployment impractical in real farm environments. Motion detection has been used to identify whether or not animals are active, but often fails to identify subtler behaviors such as nursing. Wearable sensors can solve these problems, but the social behavior of the animals limits device longevity.

PigNet is the first system to use structural vibration to monitor animal behavior. Our approach relies on the idea that animal activity creates unique vibration patterns in the structure of their holding pens. For example, when a pig walks, their footsteps create vibration in the pen structure. When they lie down, their weight changes the natural vibration of the structure. By sensing this vibration, we can infer the different activities of the animals. We use geophone-based sensors attached to the floor of a pig pen to sense the structural vibrations generated by different animal activities.

We monitor the farrowing (birth) and pre-weaning period, focusing on activity detection that relates to piglet survival. Each farrowing pen that we monitor contains a single sow (a mother pig) and several piglets. When a sow is ready to give birth, she is moved to an individual farrowing pen where she remains and nurses her piglets for three weeks. First, we detect lying activity of the sow, which can be used to predict onset of farrowing. Studies show that monitoring the farrowing process can halve the mortality rate during this time [27]. Second, we determine when the piglets nurse, a crucial time for the health of the piglets [63]. If we can track piglet nursing, then we can alert the farmers when the piglets are being underfed. Third, *PigNet* gives a pen-level metric of piglet growth, which can be used to help farmers determine if a pen is progressing normally. Traditional pig growth tracking relies on farmers manually observing piglets, which is costly, time-consuming, and unreliable. In addition, manually handling the piglets to weigh them causes stress and may expose them to health risks [55].

The key focus of our work is on improving the robustness of our system to withstand physical and algorithmic faults that occur in the challenging environment of an operational pig farm.

Physical fault tolerance describes the robustness of our hardware system to *environmental damage*. Over several iterations of our hardware, we improve its robustness to node failure and increase physical node protection. To achieve this robustness, we also focus on simplifying our inexpensive sensor nodes, allowing us to have multiple nodes that we can use as backups in case of failure.

Algorithmic fault tolerance describes the robustness of our algorithms to *sensing unreliability* due to the deployment environment. This can be caused by noise from temporary environmental changes (e.g. vibration from the sow urinating on a sensor), or differences in the structural response because the sow is lying in a different area of the pen. We also found differences in different sensors' data distributions due to unavoidable differences in their installation (e.g. sensor tilt, placement on the farm floor, or damping due to the attachment method of the sensor). To address these differences in the sensing nodes, *PigNet* performs individual analysis on each sensor before combining the results.

We collaborated with Betagro Group to deploy our system at an operating pig farm in Lopburi, Thailand [6, 12, 37].

The main contributions of this paper are:

(1) The first system that uses structural vibration to sense animal activity, to the best of our knowledge.
(2) An analysis of physical phenomenon and vibration signal characteristics in order to identify pig activities and track growth using structural vibrations.
(3) Deployment and evaluation experiences of our sensing system, including descriptions of three iterations of hardware and how they survived the environment, and a characterization of the system's performance at different sensor locations and configurations in three different pens.

The rest of the paper is organized as follows: We introduce our system in Section 2. We describe our evaluation and its results in Section 3. In Section 4, we discuss our deployment experiences, how we improved our hardware over multiple iterations of our system, and how the performance of our system varied with different sensor placements and configurations. In Section 5, we discuss related work and how our system differs from previous research. Finally, in Section 6 we conclude our work.

2 STRUCTURAL VIBRATION SENSING SYSTEM FOR PIG PENS

The main goal of *PigNet* is to produce a robust, failure-tolerant structural-vibration–based sensor system that can (1) reliably transmit information in a harsh environment without breaking down (*physical fault tolerance*) and (2) extract information about the pigs' activity and growth, even with varying levels of sensor reliability (*algorithmic fault tolerance*).

Our system consists of three main modules, as shown in Figure 1. The Redundant Sensing Module acquires the vibration signal via geophone sensors affixed to the underside of the pen (Section 2.1). Here we incorporate protective hardware and high sensor redundancy to maximize *physical fault tolerance*. Because of installation limitations and the nature of the structural environment, we cannot assume all our sensors will have the same connection to the structure around them. Therefore, our next step is to analyze each sensor individually in the Per Sensor Analysis Module. Here we use physical knowledge of structural vibration and pig behaviors

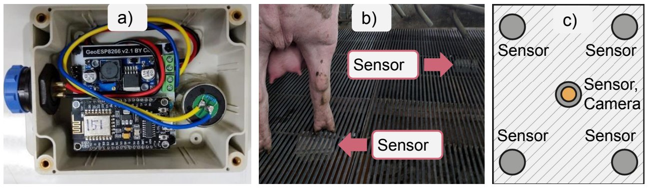

Figure 2: (a) Our waterproof sensor box, with sensor inside (in configuration 1) and waterproof connector for power. (b) Our sensor installed on the underside of a pig pen. (c) A diagram of the location of our sensors and ground truth camera in a farrowing pen.

to characterize different types of swine activity. This is elaborated on in Section 2.2. Finally, in the Combined Sensor Analysis Module, we combine sensor outputs to maximize overall sensor reliability, contributing to the *physical and algorithmic fault tolerance*. This framework can be implemented in different ways depending on our goal. We use it to assemble a daily monitoring profile for the pig pen, including the growth stage of the piglets (Section 2.3) and precise nursing and sow lying activity throughout the day (Section 2.4). Here we achieve *algorithmic fault tolerance* by incorporating redundant data from multiple sensors, and by using a weighted voting method with automatically detected weights to ignore missing sensors and accommodate varying levels of noise in our data.

2.1 Vibration Sensing Hardware Overview

One of the main challenges of our hardware, which is shown in Figure 2, is its ability to withstand environmental damage from the harsh environment (*physical fault tolerance*). We accomplish this by improving hardware durability to prevent sensor failure, and by designing for redundancy when sensors do fail. These efforts are informed by the lessons learned through three deployments at the pig farm [6]. We discuss these lessons and efforts to increase physical packaging in more detail in Section 4. Here we focus on the hardware design decisions in our sensor nodes. In short, despite efforts to protect the sensors from both their environment and the sensing subjects, we expect our hardware will incur damage from both sources over time. Therefore, we also designed the nodes to be easily repaired or recover from failures.

The simplicity of our sensors contributes to their robustness. By using small nodes with low processing power, they can restart quickly and without intervention after errors such as temporary power loss, signal degradation, overflowing buffers, and minor node damage (e.g. water ingress). Additionally, we can place several within each pen for redundancy, while utilizing all nodes for recognition when available.

Geophone Sensors: Our sensing nodes rely on geophone sensors [60] to detect the structural vibrations described in Section 2.2. Geophone sensitivity to subtle motion falls within our target sensing range (10^{-4} to 10^{-3} m/s). Geophone sensors have many advantages in the smart farming scenario. They are able to detect both movements and position changes of the pigs, including small movements such as piglet head bobbing that occurs with nursing, which a camera may not easily detect, since piglets are very small and often obscured by the sow. Because we detect low frequencies to analyze ground movement, we are able to have a sample rate between 50 and 500 Hz, much lower than the standard 8 kHz or 16 kHz of a microphone. This allows us to have redundant sensors and to upload data offsite for processing without being limited by low bandwidth or unreliable data connections, which are common in remote farm environments.

2.2 Characterization of Pig-induced Structural Vibration

When a pig steps or lays down in their pen, their interaction with the structure induces the structure to vibrate. When a mature pig (approximately 300 kg [32]) stands versus lies on the structure, the load on the structure changes significantly. When the pig stands or steps, the load can be modeled as a point load, while when the pig is lying down, the load can be modeled as a uniformly distributed load. This alters the structural vibration response under the same support condition. In a 2 m × 1.8 m individual pig pen, this change in load distribution directly impacts the structural ambient vibration, which can be detected via vibration sensors attached to the surface.

The surface-mounted vibration sensor captures these changes in surface ambient vibration. When the load distribution changes, the modal properties of the structure (e.g., fundamental frequencies, mode shapes, damping ratio) shift, changing the frequency response of the ambient vibration. In addition, when there is excitation (e.g., a piglet running) applied as dynamic point load, this induces the surface to deform and un-deform, which generates predominantly Rayleigh-Lamb waves [67]. Piglet nursing and piglet play induce waves of this type. These waves propagate through the pen structure and can be captured by the vibration sensor as impulsive signal segments.

This physical knowledge validates our observations in the raw data and inspires our algorithm for activity detection. We use the frequency characteristics of the load distribution change for sow lying detection, while our knowledge of impulsive signal propagation enables the detection of piglet nursing. Both of these help us track piglet growth, which is characterized by impulsive activities from heavier and heavier piglets.

2.3 Pre-Weaning Piglet Growth Tracking

Long-term pig monitoring over the pre-weaning period is essential to increasing the productivity of pig farms. Because piglets' health states are reflected by their activity, we can establish long-term health profiles based on their day-to-day behavior patterns. We create a pen-level metric of piglet growth based on their combined weight and activity. Non-nursing piglet activity is primarily caused by play, and higher levels of pen-play are correlated with healthier, higher-weight litters [13]. Our approach to monitoring piglet growth maximises *physical fault tolerance* by having redundant sensors, and choosing the sensors with the best reliability for our analysis.

Monitoring piglet growth patterns during the pre-weaning period is challenging because changes in the pigs differ from day to day and their movements are multi-directional. As a result, our ground-truth camera is unable to capture the characteristics of their behaviors, especially when monitoring from only a single location.

On a daily basis, piglets are active at different times for different activities such as suckling, playing, resting, etc. The intensity and type of activity varies as their body weight increases and behavior patterns change. Figure 3 shows a clear visual difference in piglet growth over the pre-weaning period. However, this growth occurs slowly over time and is hard to see day-to-day.

To address this challenge, we leveraged the insight that multi-modalities "observe" the pigs from different perspectives, and we used vertical structural vibrations to compensate for the limitation of the horizontal-view camera. We used our data collection timestamps to analyze our vibration signal with respect to both the number of days since farrowing and the time of day, to track both daily patterns and longer-term trends that we can correlate with the piglets' overall weight gain and therefore growth. To establish a thorough profile of piglet health, we gather data over two time scales: (1) different time slots in each day and (2) different weeks in each pre-weaning period. These hourly and weekly separations enable long-term pig monitoring with timely checkpoints.

The framework of long-term pig activity monitoring using vibration based sensing is presented in Figure 1. In the following sections, we introduce the long-term monitoring system in three modules: (1) per-sensor physical characterization of the piglet activities, (2) per-sensor supervised clustering, and (3) combined sensor analysis with concatenation.

2.3.1 Per-sensor Physical Characterization of Piglet Activities. In this module, we characterize the piglet activities by extracting physical features from the pre-processed floor vibration signals. These features include time-domain, frequency-domain, wavelet-domain features and signal energy, which represent different physical aspects of the piglet activities respectively. Since we are focusing on the long-term activities, we first low-pass filter and sub-sample the data to reduce the processing time. Although information loss occurs during the sub-sampling process, it significantly improves the system efficiency without sacrificing the low frequency piglet activity information.

Time-domain features (90% quantile, median and standard deviation of the signal magnitude; signal energy), indicate the intensity and variation of the pig activities. As presented in Figure 4, the magnitudes of the signals are much higher from 7-9 a.m. and 3--6 p.m., which corresponds to the daily food refill schedule. This activity excites the sow and triggers intensive piglet activity. The signal energy represents the energy of the floor vibration generated by the pigs, as captured by a single sensor from each pen. This is correlated to the piglets' weight gain throughout the pre-weaning period.

Frequency-domain features (90% quantile, median and standard deviation of the signal magnitude for frequency bands 0-5, 5-10,10-15,15-20Hz) are used to characterize activity types. As described in Section 2.4.1, we use the insight that pig nursing and lying activity are characterized by different movement frequencies, and thus are reflected by the frequency-domain features. These features allow the system to separate different activity patterns in the long term as shown in Section 3.3.2

Time frequency-domain features (wavelet coefficients) are defined as the signal magnitudes after the wavelet transform, which represent the vibration characteristics in both time and frequency domain. Therefore, wavelet coefficients capture the relationship between activity intensity and type through time-frequency correspondence.

Figure 3: Nursing piglets just after birth, and right before weaning, 20 days later. The photos are from our ground truth camera and use the same level of zoom.

With these features, we can relate the ground vibration with the physical characteristics of the growing piglets by comparing them with the ground truth, which further enables prediction and interpretation on the piglets' activities using vibration sensing.

2.3.2 Per-Sensor Supervised Learning with Clustering. With the features extracted from the vibration signals, we separate the activity patterns based on different times of day and different weeks in the pre-weaning period to better monitor pig growth and status. To visualize the clusters, we conduct principle component analysis (PCA) to reduce the dimension of the feature space. With the clusters as our reference for healthy piglets, we can detect abnormal behaviors represented by points that deviate from the cluster centroid. Once we collect enough data points through long-term monitoring, the clustering approach enables the prediction of active period and growth stage, as well as detection of unhealthy piglets and abnormal behaviors. We predict the growth period using K-nearest neighbors (KNN) because it captures the gradual change between different growth stages and time by considering nearby points in classification. With this knowledge, breeders can understand the growing status of the piglets, which help them to select good mother pigs to increase productivity and detect anomalies to decrease the pre-weaning morality rate. We present the evaluation results from our deployment in Section 3.3.

2.3.3 Combined Sensor Analysis by concatenation. Because we take a macro view of each day while evaluating growth, we do not need to worry about *sensor unreliability* due to environmental changes, which are intermittent and average out over the course of the day. However, it is still important to have physical fault tolerance with sensor redundancy, as sensors may lose connection or break. We choose the sensors with the best connectivity, and then provide a report from each sensor on the active periods and growth stage for that day. This give the farmers more information to use their extensive behavioral knowledge of the pigs to interpret the results.

2.4 Nursing and Lying Detection

PigNet's nursing and lying detection algorithm is designed to maximize *physical fault tolerance* by dealing effectively with missing sensors. At the same time, it increases *algorithmic fault tolerance* by effectively combining multiple sensors for knowledge redundancy while handling different sensor data distributions due to changes in environmental noise.

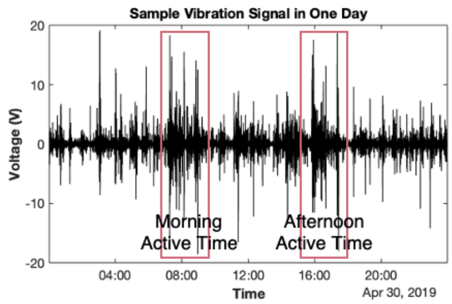

Figure 4: Sample vibration signal over one day with morning and afternoon active times

PigNet recognizes lying and nursing activity with up to two second precision. Our overall procedure is similar to the piglet growth tracking, but with different implementation choices to reflect the more precise time frame and our increased physical and behavioral knowledge. First, in the per-sensor analysis module, we do time-frequency characterization with emphasis on capturing the modal distribution changes caused by the sow's change in position, and preserving the stationarity of the data caused by her movements. Then, in the combined-sensor analysis module, we classify our features with respect to each sensor and category, which handles varying data distributions. Next, we use a feed-forward weighted voting technique to combine our different sensor predictions, which learns the best weights for combining each sensor. Finally, we use a temporal smoothing algorithm to better represent the sequential nature of our data and incorporate our knowledge of pig behavior.

2.4.1 Features for Activity-Induced Load Changes Characterization. As described in Section 2.2, different pig activities create unique vibrations in the structure of their pen. We effectively characterized this data with the feature selection process in Section 2.3.1, however, in this section we use two-second windows instead of several hours long, because our data is non-stationary and we want fine-grained detection of when activities change. For example, the intermittent Raleigh-Lamb waves caused by nursing provoke short, higher frequency impulses that would be harder to detect in a longer window. The Fourier transform of the standing data has, in general, a higher, wider frequency band caused by dynamic load. In contrast, lying has the narrower frequency band we would expect from a uniformly distributed load, concentrated about 25 Hz — possibly the fundamental frequency of the structure.

2.4.2 Per-Sensor Supervised Learning with SVM. We use a support vector machine on our features to build each classifier. SVM is an appropriate choice because it is a standard machine learning algorithm commonly used for activity detection [28]. It does not require large amounts of labeled training data, and the kernel function $\phi(\cdot)$ in nonlinear SVM lets us build models with high class separability and generalization ability, even when we don't have linearly separable data [14]. We have a lot of outliers in our data (about 12%) due to clipping, which was a tradeoff we made to prioritize precision of low amplitude data at the expense of range. As such, we chose to use the radial basis function kernel with our SVM, as it is nonlinear and generally the most robust to outliers [26].

2.4.3 Weighted Voting Robust to Missing Sensors. A sensor's response may change over time due to environmental factors. For this reason, as well as the potential for sensors to fail, we assume each sensor will have unpredictable levels of performance. Instead of directly using the SVM predictions, we use the confidence scores as initial weights in our weighted voting module, which can both take advantage of redundancy and is robust to missing sensors. We use a simple feed-forward neural network with one fully-connected layer to learn weights and combine our classifiers.

2.4.4 Pig Behavior-based Sequentialization. While the small time windows we chose are more effective in characterizing the non-stationary components of complex activities, they don't reflect the timing of the activities themselves. Nursing lasts for at least a minute, while lying often lasts even longer. We incorporate this behavioral knowledge using a time-based moving consensus filter to smooth the results. If a prediction is reliable, we know that it will be followed by more predictions of that label. Therefore, because our bouncing issue is so severe, we use a consensus measure to decide when to switch between predictions. Starting with the first value, we continue to hold to that value until we encounter N_{label} predictions in a row of a new value. Then we switch to that prediction, starting with the beginning of the consensus, and continue to populate the new array until we encounter a new consensus, and so on. This effectively debounces our data predictions. We use behavioral knowledge about the sow's nursing and lying to determine an appropriate N_{label} for each activity.

3 REAL-WORLD EVALUATION AT AN OPERATING PIG FARM

We deployed *PigNet* for three months at a Betagro Farm in Lopburi, Thailand, from April 2nd - June 9th, 2019. As the animals used in the study were not used soley in this collaboration and were not supported by our funding, our institutions' IACUCs determined that a protocol review was not needed for this study. We did not interact with or change the animal environment in any meaningful way, but simply monitored them from afar while the farm continued normal operations.

3.1 Data Collection

We installed the sensors in two farrowing pens and one farrowing crate, designed for a single sow and her piglets. A farrowing pen is shown in Figure 2b. Each pen has ten sensors installed on the underside of the floor of the pen, two each in five different locations, as shown in Figure 2c. We use two configurations for the placement of the geophone sensors. In the first, we glue the sensor directly to the pig pen, connecting it with a waterproof cable. In the second configuration, we put the sensor inside the waterproof box to better protect it from the elements, at the cost of a weaker connection to the structure.

3.2 Ground Truth Labeling

3.2.1 An Indirect Approach to Piglet Growth. For growth tracking, we used the weight gain of the piglets over the pre-weaning period, which was collected by the farmers when they were born and at weaning. The piglets gained an average of 66kg per pen over the farrowing period. We also used the timestamps on our data for ground truth of time of day and growth week. In this way we did not have to manually label our data for growth tracking, and were able to test all of our available data. See Section 2.3 for more about growth tracking.

3.2.2 Behavioral Labeling of Nursing and Lying. For nursing and lying detection, a camera aimed at each pen collected video of the pigs' activities. This video was then watched by the researchers and labeled with the ground truth using Boris Labeling Software [21]. This time-consuming process took many hours, and gave us personal experience in the importance of automated monitoring. We chose pens in an area that happened to be well lit even at night, so that we were able to label ground truth for the pens at all times of day. We labelled a 72-hour period from three different pens with these fine-grained lying and nursing labels. In addition, we tested farrowing detection on three days of unlabeled data from one pen shortly before we saw a sow give birth in that pen. Most of the time the farmers moved sows with just-born piglets into the pens, so we only occasionally had access to pre-farrowing data.

Sow Lying. We define lying to be any time the pig was lying down, as opposed to standing, sitting, or moving between positions.

Defining Piglet Nursing. Piglet nursing tends to occur in intervals of 45–60 minutes, and takes about 20% of the day in indoor pens [4, 30]. A nursing session is defined by four stages, in which the piglets approach the udder, suckle to stimulate the udder, receive the milk, and continue suckling post-milk. It is difficult to distinguish the final three stages by sight. Prior approaches to this issue when monitoring piglets opted to disregard the individual phases, instead tracking each overall suckling period. Thomsson et al. define "nursing/suckling" to be any time when at least five piglets are suckling, while Valros et al. define it as any period longer than 60 seconds where at least half the piglets are suckling [63, 66]. We chose to use the definition given by Thomsson et al. of at least 5 piglets suckling, as it is straightforward and will be consistent across cages. We also added the time constraint of 60 seconds to increase the likelihood that the session contains a let down period.

Our nursing labels lack the precision of our lying labels due to their reliance on subjective human judgement and a top-down camera. Piglets frequently fall asleep while still suckling, and it can be hard to tell if they are sleeping or nursing. Sometimes one piglet was hidden behind another in the frame, or behind part of the sow. We checked our nursing frequency and duration after labeling and found they were within the expected range [4, 30].

3.2.3 Hardware Set-up. Our system uses SM-24 geophones, LTC6910 programmable amplifiers, and MCP3201 ADCs, all connected to NodeMCU boards, which are low-cost open source microcontroller boards for IoT platforms with onboard Wifi [17, 39, 45, 60] using an ESP8266 [62] main chip.

We use a BeagleBone Black [8] connected to a TL-MR6400 [64] router to form the network which the peripheral sensors connect to over WiFi. We use MQTT for message passing, which requires only a small code footprint, processing, and network overhead to transmit the captured data [1].

Our network is configured in a simple star topology, but could be easily reconfigured for better scalability.

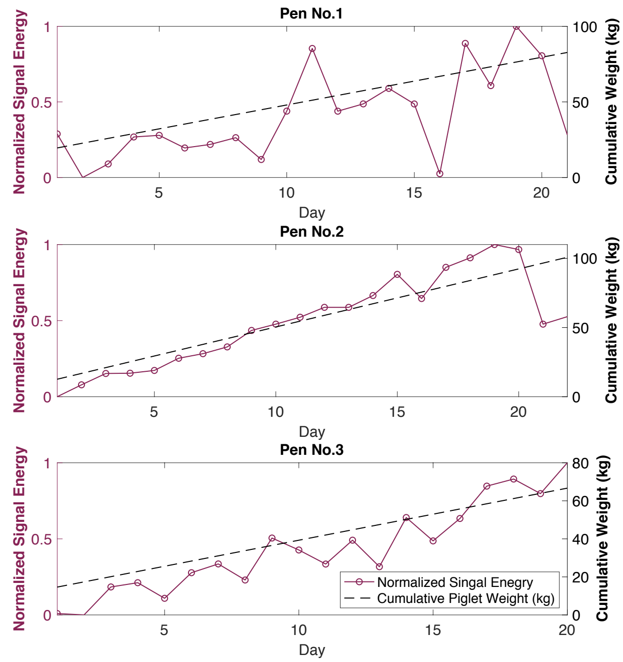

Figure 5: Correlation between normalized signal energy of a single sensor and piglet weight gain for 3 pens. The lower correlation for pen No.1 is due to a connectivity issue with the sensor on day 16, which caused the energy to drop.

3.3 Pre-Weaning Piglet Growth Tracking

We design our evaluation scheme for pre-weaning piglet growth tracking by defining the following two goals: (1) demonstrate the capability of the vibration sensing approach to infer physical characteristics of the piglets; (2) validate the feasibility of our clustering approach for long-term activity monitoring.

For our experiments, we utilized three 3-week pre-weaning periods each in three different pens. This was all of the data available during our 3-month deployment, as the pens often sit empty for a few days in between litters. Three weeks is the entire time the newborn piglets spend in these pens from birth. We first pre-process the signal with a 20 Hz low-pass filter and down sampling rate of 10 to reduce the sample frequency to 50 Hz to maintain the structural vibration from piglet activity, which is contained mostly in low frequency bands (0 – 20 Hz).

3.3.1 Weight Gain and Signal Energy Correlation. To quantify the relationship between vibration signals and piglets' weight gain, we conducted a correlation analysis between the signal energy variation and weight increase over the pre-weaning period.

We compare the weight gain with the normalized signal energy of a single sensor per pen as shown in Figure 5. The piglets are weighed at the beginning and the end of the pre-weaning cycle (dash line). Normalized energy of the vibration signals (solid line) are obtained after each day. The correlation coefficients are 0.62, 0.86, 0.94 respectively. The lower correlation for pen 1 is due to a connectivity issue with the sensor on day 16, which caused the energy to drop to almost zero. This reinforces our need to accommodate sensor failure. For pen 2 and 3, there are minor fluctuations

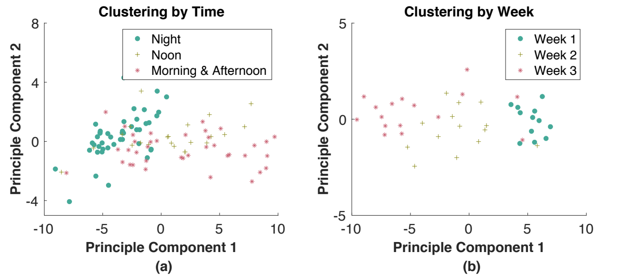

Figure 6: Cluster visualization using PCA: (a) Different time in a day (79.1% test accuracy) (b) Different Weeks in a Pre-weaning Period (81.8% test accuracy)

in signal energy due to differences in activity intensity across different days. To prove the correlation relationships statistically, we conduct hypothesis testing using t-statistic and set our null and alternative hypothesis as $H_0 : \rho \leqq 0, H_A : \rho > 0$. The p-values are $2.6e^{-3}$, $2.6e^{-7}$, $1.2e^{-9}$ respectively, which are all below the significance level of 0.05. Therefore, we can reject the null hypothesis and conclude that there is correlation between signal energy and piglet weight gain.

3.3.2 Active Period and Growth Stage Prediction. In our clustering evaluation, we focus on the accuracy of each single sensor instead of all sensors because this allow us to be flexible in dropping any sensor that fails during the long-term deployment. To combine different sensor outputs, we select the sensors that maintain connectivity and function throughout the targeted period and plot them in the same figure. As an example, Figure 6 is obtained from sensor 162 and 164 from pen No.2, which maintains good connection and continuous record throughout the cycle.

To prevent our features from biasing towards the outliers, we calculate the 90% quantile, median and standard deviation of the signal magnitudes in each domain to represent the piglet activity patterns over the pre-weaning period and over each day. To visualize the discrepancy between the clusters, we conduct PCA to compress the feature dimensions into two principle components.

Active Time Prediction: In Figure 6(a), we observe the clusters by plotting principle components to track activity changes during different time slots. To demonstrate that data points with similar features belong to the same cluster, we evaluate the clustering accuracy using K-nearest neighbors (KNN), which gives us 79.1% accuracy for different times of day. There is a gradual change from active hours (i.e., morning and afternoon) when sow feeding occurs, to the inactive hours (noon and night) where piglets and the sow are either sleeping or with minor movements. We observe a clear boundary between night and noon, but there are multiple points from morning and afternoon that are mixed into the other two clusters. This is because piglets are not always active during feeding hours. They tend to alternate between walking/running and resting.

Growth Stage Prediction: In Figure 6(b), there are three distinguishable clusters between different growth periods as the piglets go through the 3-week pre-weaning period. The KNN model gives 81.8% accuracy in growth stage prediction. From the first week to the third week, the cluster moves from right to left, which indicates the gradual growth pattern due to their weight increase and

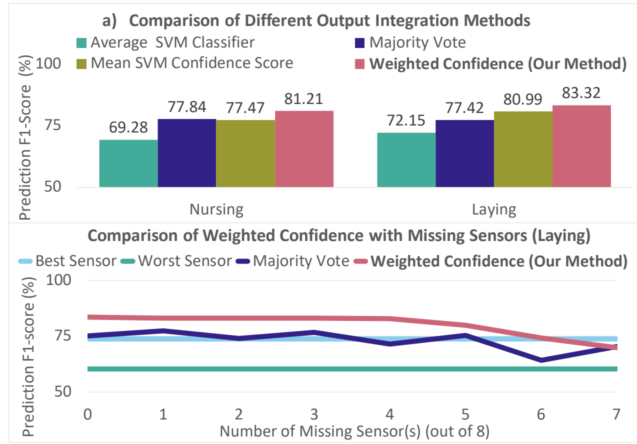

Figure 7: (a) Prediction Accuracy for Nursing and Lying Activities for several methods of combining our SVM classifiers, including our chosen weighted confidence method. We conclude that combining sensors effectively increases fault tolerance by adding information, and our Weighted Confidence method is effective at detecting appropriate weights for each sensor. (b) shows us that our Weighted Confidence method is equally robust to missing sensors as a majority vote algorithm, while being more effective at combining sensors for data redundancy.

changes in behavior patterns. The results from the clustering provide references for the active time and growth stage of the healthy piglets, which allow us to detect abnormal behaviors that result in feature points that deviate from these clusters.

In summary, we show that there is correlation between vibration energy and piglet weight gain, and the clustering method shows clear trends of activity changes throughout each day and each pre-weaning period.

3.4 Nursing and Lying Detection

The nursing and lying recognition component of *PigNet* requires fine-grained labeled data to train and evaluate. We evaluate our results on a 72-hour period from three different pens to show the robustness over multiple days and multiple pens. Because we have significantly imbalanced data, we use the unweighted mean of the F1 score as our accuracy measure, giving our smaller class equal weight to the larger one. Our accuracy graphs all start at 50% to show the improvement compared to random guessing.

3.4.1 Evaluating Weighted Voting Robust to Missing Sensors. We evaluated the effect of *PigNet*'s weighted voting algorithm on *physical and algorithmic fault tolerance* by testing its ability to combine multiple sensors and be resilient to missing sensors. We tested against three baseline methods for combining our per-sensor analysis results. This is shown in Figure 7a. The first baseline, in teal, is the average accuracy of the individual SVM classifiers, what we would expect if, instead of combining knowledge, we randomly picked a single sensor to use. The second baseline, in navy, shows the result of a simple majority vote. Here we can already see evidence that adding redundancy by combining sensors is very useful,

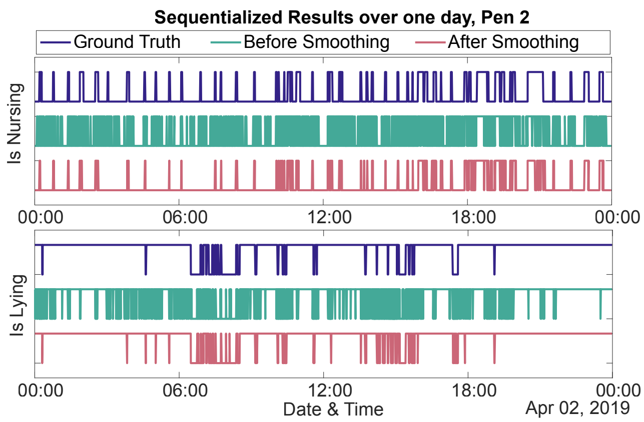

Figure 8: The ground truth labels for each activity over the course of a day. Each line goes up when the activity is detected, and down when it is not detected. Below that, we show the output of our weighted confidence method, which, even with over 80% accuracy, does poorly over time because it quickly bounces back and forth between predictions. Last, our smoothing method is shown, which does a much better job of localizing the activities in time.

since individual sensors are not always reliable on their own. The third baseline, in olive, takes the average confidence score instead of the average output, and converts that into a prediction. Using the confidence scores allows us to give higher weight to sensors that are trusted more by their classifiers, which helps adapt to unpredictable sensor performance as discussed in Section 2.4. This does not seem to have much effect on the nursing classifier but does help with lying prediction. Finally, we show the accuracy for our weighted confidence metric, which uses a feed-forward network to train the weights for each sensor. This method proves to be more effective at detecting the relative reliability of sensors.

Our weighted confidence method continues to be robust if we lose some sensors entirely. We tested this method with from 1 to 7 sensors missing, with results shown in Figure 7b. We found the F1 score to be at least as consistent as the majority vote method, which is robust to missing sensors since it can easily ignore them. We can see that after five sensors are missing the accuracy starts to drop, and eventually it meets the majority vote method, which we would expect, since at only one sensor left there is nothing to combine, and we just get the average accuracy from using a single sensor. We can conclude from this that our weighted voting algorithm accomplishes both goals. (1) It increases *algorithmic fault tolerance* by effectively combining sensors to maximize information in a context of sensing unreliability, and (2) it is resilient to missing sensors, which increases our *physical fault tolerance* to environmental damage.

3.4.2 Evaluating Sequential Smoothing. Finally, we perform our sequential smoothing algorithm, which uses temporal and behavioral information to better judge the start and stop time of activities. Figure 8 shows the ground truth labels for each activity over the course of a day. Below that, we show the output of our weighted confidence method, which, even with over 80% accuracy, does poorly over time because it quickly bounces back and forth between predictions. This is an effect of the trade-off we made to better capture time information for non-stationary data with small windows. Last, our smoothing method is shown, which does a much better job of localizing the activities in time.

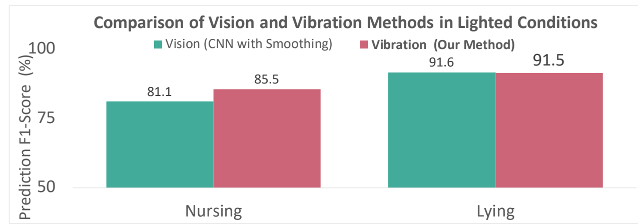

Figure 9: Results of Vision-based vs Vibration-based pig activity detection. Our Vibration-based method matches or slightly outperforms the Vision-based method in similar conditions.

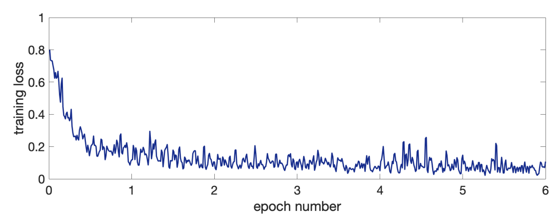

Figure 10: The cross entropy loss for the first six epochs of training the final layer of our vision-based model. (We adapted the Resnet18 CNN, pretrained on Imagenet). We can see that the model converges quickly.

	Storage (one minute)	Training Time
Vision	12 mb	504 seconds
Vibration	1 mb	125 seconds

Table 1: Comparison of processing time and storage needs for vision and vibration-based methods for a single pen. The vision method uses a single camera, while the vibration-based method combines four geophones. The vibration sensor data takes up much less storage, which would add up quickly on a big farm with many pens.

3.4.3 Comparison with Conventional Vision Analysis. We compare our vibration-based short-term lying and nursing detection with using an image-based classifier. For the image-based classification, we use Resnet18, a deep convolutional neural network, pretrained on the Imagenet dataset [16, 25]. We appended a single fully-connected layer to the pre-trained model, which we optimized to our data using cross entropy loss and stochastic gradient descent, implemented in Pytorch. This is a widely tested industry standard. We trained for 10 epochs with about 5000 frames of data from a single day. The cross-entropy loss over the first six epochs is shown in Figure 10. We evaluated with data from a different day in the same pen. We debounced the frame-level results with the same sequential smoothing algorithm as we use for our vibration analysis. We compared those results to our vibration-based method for the same day and pen. We found that with lying the algorithms performed equally well, but that our vibration-based method was more adept at classifying nursing. This makes sense given the difficulty we had manually labeling lying with the cameras: piglets sleeping next to the sow often look very similar to piglets nursing, and if humans have a hard time distinguishing the difference, a neural network might have even more trouble.

We also compared the data storage and training times for the two algorithms, which were both implemented in python on the same computer, with an NVIDIA GeForce RTX 2070 GPU [46]. It is possible that a future version of either method would work with a lower sample rate (and less data) and could be written to be slightly faster. Even knowing that this is an imprecise metric, it is clear that the vibration sensors take up far less storage, and would therefore also require much less bandwidth to send data. A large pig farm may have hundreds of farrowing crates [58]. Constantly monitoring all of these with cameras could become infeasible due to all this data. Using vibrations as opposed to images becomes critical in the remote farm environment where unreliable data connections do not provide sufficient bandwidth to upload video for offsite processing [6]. Additionally, when implementing this comparison, we chose a pen in an area that happened to be well lit even at night. Not all of the pens have good lighting, and choosing to leave the lights on all night could cause the pigs stress as well as add significant electricity costs on a big farm[23]. The vision-based method has the advantage that cameras are less susceptible to the sensing unreliability and varying data distributions we experienced with geophones. While *PigNet* has achieved good fault tolerance to sensing unreliability, we have yet to train and test in different pens. We are optimistic that this issue can be effectively addressed in future work by using transfer learning to adapt the data distributions, as we demonstrated with footsteps in a previous work [41].

3.4.4 Farrowing Detection and Final Nursing and Lying Results. Our final test results for classifying nursing were 85.5% (F1 score). Our average ground truth nursing duration per day was 270 minutes, which is within normal range [66]. Our average absolute duration error was 17 minutes per day, or about 6%. For lying detection, we achieved an average F1 score of 91.5%. Most days, the sow was lying for about 21 hours, or almost 90% of the day. Our average absolute duration error for lying was 14 minutes, or about 1%. A sow lies between 10% and 20% less the day before farrowing, so this duration error is well within the range necessary for farrowing prediction. We tested our lying algorithm on a pen with a single pregnant sow, three days before, two days before, and one day before farrowing. *PigNet* output durations of 84%, 87%, and 72% of each day spent lying, respectively, showing that our monitoring accuracy is adequate for a real-world application on an automated farm, as we can effectively detect the sow's changing behaviour caused by approaching parturition, and predict farrowing a day in advance.

4 DEPLOYMENT EXPERIENCES AND LESSONS LEARNED

Over the course of three deployments, we gathered data which allowed us to steadily improve our hardware, resulting in a robust yet sensitive system that can stand up to its challenging environment while still providing reliable data. Here we describe our design decisions and lessons learned through multiple deployments.

4.1 Environment and Animal Effects

Before our first deployment, we knew that the physical environment of the pig pen would provide our sensors with serious environmental challenges. However, it was impossible to fully anticipate how our sensors would handle exposure until deploying and witnessing the environmental damage first-hand. The two primary causes of damage in the pig pen are water and chemicals. Pig urine and excrement contain chemicals that damage our equipment. In addition, the liquid from animal waste, drinking water, and the jets used to clean the sewers frequently drench the area where our sensors are deployed. Our sensors are made of metal and sensitive electronics, which can be short circuited by water as well as degraded by frequent water damage and chemical exposure. They also become less sensitive to the movements of the pigs above them if they are submerged in a pool of waste. We needed to make our sensor deployment watertight and resistant to chemical damage, while still maintaining enough sensitivity to accurately track the pigs' movements. Further, we discovered a third cause of damage: cleaning jets powerful enough to dislodge our sensors from the structure. As such, in addition to being chemical-resistant and watertight, our sensors also need to be securely fastened.

Sensor location and power supply proved to be an additional challenge. When deciding where to place the sensors, we also had to account for animal behavior. We placed the sensors under the floor of the pen so the pigs could not disturb them, but the sensors still needed a power source, because the sensors must be able to operate through an entire farrowing period without interaction. Wiring the sensors to the building's power supply came with its own challenges, however. In one instance, an escaped pig ran into the power supply module on the wall and pulled the cord, cutting power to two of the sensors. Ironically, in this case, the pig activity that we set out to monitor proved to be our hardware's undoing. To reduce the attraction of the nodes to the pigs, we removed any indicator LEDs on the hardware, as we noticed the pigs occasionally congregated around the nodes looking at the LEDs.

4.2 Iterations of Hardware Protection

We upgraded our hardware's durability throughout three iterations of system deployments.

4.2.1 Version 1. Figure 11 shows the design of our first deployment, where we sealed the concrete slab and plastic box with insulating foam and left a hole for Ethernet and power cables. The sensing device and sensor were glued to the concrete slab. Desiccant packs were placed in the plastic box to reduce the potential leaks. Once the seal was dry, we flipped the concrete slab and placed it as shown in Figure 11 (b). All the sensors stopped transmission within one week, although the LEDs were still blinking. We concluded that the

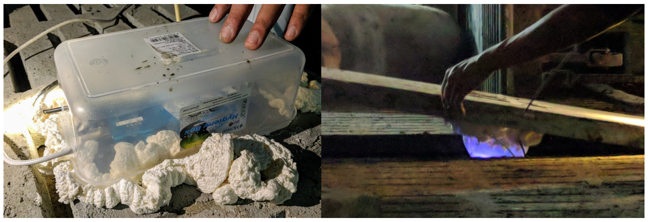

Figure 11: Deployment Version 1.

Figure 12: Deployment Version 2.

Figure 13: Two "after pictures" show how far our hardware protection has come. On the left, a sensor from Deployment 1 that was flooded with dirty water a few days after deployment. On the right, a sensor from Deployment 3 after months of use. Although there are stains inside the box, this sensor (which was installed inside the protective box) is still functional. It stopped transmitting when a pig escaped its pen and damaged the power cable leading to the wall.

failures (see Figure 13, left) were due to insufficient waterproofing caused by underestimating the water pressure and possibility of submersion when animal waste accumulates.

4.2.2 Version 2. For version two (shown in Figure 12), we upgraded our waterproof boxes to IP66-rated protective boxes with protected cable connectors. IP66 rated boxes are fully protected against dust and against strong jets of water [9]. We connected the geophones and power to the boxes with insulated wire through the waterproof connectors. As before, we superglued the boxes and geophones to the underside of the floor of the pen, and used waterproof insulating foam to further protect them from the elements. We also used more sensors to add redundancy in case of failure, installing five sensor boxes in a single farrowing pen.

In the first two weeks, three out of our five sensors stopped working. We determined that this was due to water damage caused by the corrosion of synthetic rubber seals by alkaline animal urine. Detailed information of this dataset is published [12].

4.2.3 Version 3. In our current installation, we increased the sensors' protection yet again. We replaced our IP66 boxes and cable connectors with IP67 boxes and connectors, which have a higher level of protection from liquids and corrosion: they are protected against immersion of up to one meter for up to 30 minutes [9]. We added ten sensor boxes per pen, five with the geophone outside the box and connected with wire, and five in a new configuration, with the geophone inside the IP67 box and thus better protected, at the cost of a weaker connection to the structure. The power cables run through the open sewer underneath the pig pen to a power source on the wall of the farm building. The power cables had their normal PVC cable sheath replaced with rubber cable sheath which can withstand chemical, mechanical and thermal stresses [7].

In this final installation, we lost about 10% of our sensors per month, and managed to maintain a functioning system for over three months, even with sensor loss. A comparison of our hardware after use in Figure 13 shows how far our system has come.

4.3 Effects of Sensor Positioning

To further understand the impact of structural variation on the system, we installed multiple sensors under each pig pen. We placed two sensors each at five different locations for each rectangular pen as shown in Figure 2 c. This allowed us to explore and reduce the impacts on the data distribution and examine the effect of having the sensors inside the protective box vs. attached directly to the underside of the floor.

4.3.1 Comparing Sensor Configurations. We found that the sensors inside the box had a somewhat dampened response at frequencies under 100Hz, but often showed a higher response at frequencies above that. We attribute this to the zip-tie connection between the protective box and the floor grating, which may have allowed the box to vibrate more freely than the floor itself, while also blocking some of the incoming low-frequency signal. Despite this, we found the sensors in both configurations provided equally useful data in our long-term and short-term algorithms.

4.3.2 Comparing Sensor Locations. In all the pens, the highest accuracy for classifying a particular activity depended on the location, not the sensor configuration. However, this location differed with the activity. In both Pen 1 and Pen 2, the best sensors for detecting lying were next to the feeder and the water dispenser, while the best sensors for detecting nursing were in the middle. This is likely because nursing usually happened in the middle of the pen, while standing occurred primarily at the feeding and drinking areas. We do not attempt to draw conclusions about sensor location from Pen 3, as it had a different layout and half of its sensors failed, leaving us only two locations to compare.

As shown in Figure 7, we found that we could maximise our accuracy with four sensors, so we concluded that more than four working sensors would not be needed in an installation. However, a single sensor can theoretically monitor an entire pen, and if we use our new knowledge about sensor location, we can approach that number. Our sensors failed at a rate of 10% a month, so we recommend installing two sensors per pen, and replacing any broken ones every month after weaning. With two sensors, we can combine them for *algorithmic fault tolerance* with one in each optimal location. We also have *physical fault tolerance:* if one breaks, than we still have one left. In this case, the one remaining sensor would then be less effective than having two, but since that would only

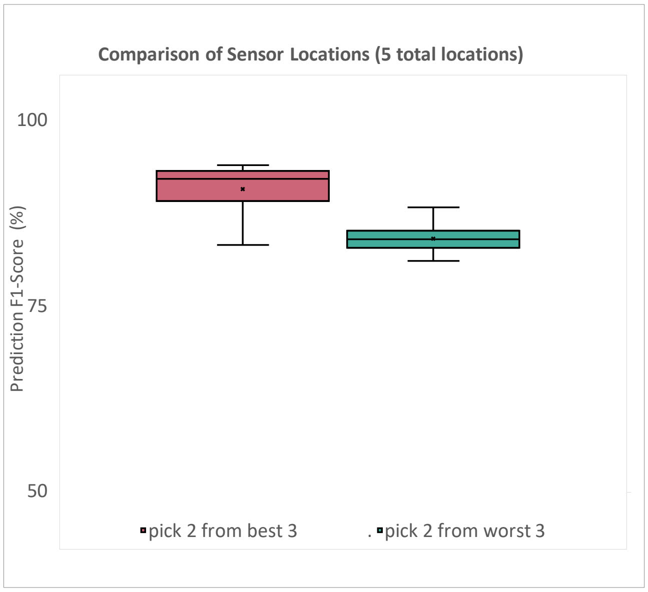

Figure 14: A box plot of the lying accuracy with two sensors chosen out of three, first in our most effective locations and second in less effective locations (as there are only 5 locations one is in both). This simulates random failure of a single sensor. Having more sensors than necessary adds redundancy to the system.

happen occasionally it would be a reasonable tradeoff for a lighter installation, especially when monitoring many pens at a large farm.

4.3.3 Adding More Sensors for Redundancy. As shown in Figure 7, we found that we could maximise our accuracy with four sensors, so we concluded that more than four working sensors would not be needed in an installation. However, this was based on using the average of all four-sensor combinations. A a single sensor can theoretically monitor an entire pen, and if we use our new knowledge about sensor location, we can approach that number. Figure 14 shows a box plot of the accuracy of lying detection when two sensors out of our three previously determined best locations are used, simulating failure of a random sensor. Next to it is the box plot when two sensors out of our other two locations and one better location are used (we only had five locations). The average accuracy as well as the minimum accuracy is higher when our locations are carefully chosen, allowing us to maintain redundancy to sensor failure while also lowering our installation footprint. The difference is not huge, however, which leads us to conclude that the combining and smoothing stages of our system help make up for the loss of accuracy from less than ideal sensor locations. Our sensors failed at a rate of 10% a month, so we recommend installing one more sensor per pen than needed, and replacing any broken ones every month in between weanings.

5 RELATED WORK

Our related work spans several areas, detailed below. We are the first to do automated monitoring of animals with structural vibration sensors. Therefore, our work is informed both by systems of animal monitoring with other types of sensors, and structural vibration based monitoring of human activities.

5.1 Animal Monitoring with Cyberphysical Systems

Much work has been done on automated animal monitoring with cyberphysical systems, with applications including migratory behavior tracking, behavior analysis and activity recognition of farm animals, animal posture monitoring, and animal estrus detection.

The most common modalities are cameras and wearable sensor systems. Cameras are almost exclusively used to detect activities in indoor domestic livestock environments such as pigs and chickens [33–35, 38, 56, 70]. These computer vision methods often have intense processing and storage requirements, making them difficult to deploy in real-time environments. They function best in well lit areas, which could disrupt animals circadian rhythms [23]. They also have line-of-sight restrictions that can hamper their effectiveness when there are a lot of animals or equipment. Wearable sensors have become the research standard in livestock monitoring for tracking cows, pigs, sheep, and wild animals [3, 15, 18, 24, 29, 36, 59, 65, 68, 69, 72]. Wearable sensors are susceptible to being chewed on by animals or damaged by social behaviors. Oliviero et al. use photocell movement sensors and force sensors installed in a pen to measure movement, and are able to predict farrowing onset [47]. So far no systems have done automatic detection of nursing. Previous long-term monitoring tracks environmental conditions, activity level and reproductive states of the livestock, which provide insights for increasing productivity and reducing loss due to disease and mortality [22, 40].

5.2 Structural Vibration based Activity Monitoring

Structural-vibration based sensing systems have been used for various indoor activity inference. The intuition is that the vibration signal that contains the information of the physical interactions at the structural surface (e.g., human or animal movements on the floor) propagates far through a solid medium, which enables non-intrusive sparse sensing [53]. As a result, various applications, including identification [52, 54], localization [43, 44], activity recognition [11, 42, 49–51, 61], and physical conditions [5, 10, 20] have been explored in this direction. However, these prior works mainly focus on indoor human information acquisition, which are often in the environments of less noise and hazards compared to the pig farm as demonstrated in this work.

6 CONCLUSION

In conclusion, we introduced the first system to use structural vibration to track animals, and the first system to do automated detection of piglet nursing. *PigNet* uses physical knowledge of the structural vibration characteristics caused by pig-activity induced load changes to detect nursing and sow lying, and detect piglet growth. In order for our system to survive the harsh environment of the pig pen for three months, we designed simple, durable sensors for *physical fault tolerance*, then installed many of them, pooling their data to achieve *algorithmic fault tolerance* even when some do stop working.

We provided an extensive discussion of the many lessons we learned from our real-world deployment. Our system predicts the growth week in the pre-weaning cycle with 89% accuracy, a metric that can be used to monitor the piglets' growth progress over the pre-weaning cycle. To help farmers monitor piglet feeding, starvation, and increased risk of crushing, we detect daily nursing activity with 85% accuracy and daily lying activity of the sow with 91% accuracy. We demonstrate that our monitoring of sow lying activity can be used to effectively predict farrowing.

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