iPig: Towards Tracking the Behavior of Free-roaming Pigs

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ABSTRACT
Many farmers and families in poor rural areas in the developing world keep pigs as a resource for income. Most of these pigs are not kept in stables but let to roam freely. While this enables poor farmers to keep livestock without vast investments and sets pigs free from stables, it also increases the transmission rate of infectious diseases among pigs and to humans. Currently, there is a lack of knowledge on free-roaming pigs' behavior. In particular, veterinarians are interested in correlations between pig behaviors and the presence of an infectious disease. In this paper, we present the iPig system, a wearable motion sensor to track the physical activity of pigs and a user interface to enable veterinarians to keep track of the activities of the pigs in a herd. The motion sensor inserted inside a pig's ear classifies its physical activities into 'walking', 'eating' and 'resting'. A daily report about pig activities is displayed to veterinarians over a user interface on a tablet device. Results of a first pilot study suggest that iPig could classify pig physical activities with an accuracy of up to 95.8%. We also discuss the rationale behind the wearable for pigs we designed following an animal-centered design methodology.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation: Miscellaneous

Author Keywords
iPig, wearable. activity recognition, animal, pig

INTRODUCTION
The increasing demand for meat has made pork grow in popularity, mainly because pigs have low associated costs to acquire and raise [11]. In particular, pigs grow faster and have more offspring than sheep and cattle, eat leftover food, and are easy to sell [6]. As a consequence, several farmers and families in developing countries such as Zambia, Kenya, Uganda and Tanzania have started keeping pigs as a resource for savings and income [6].

One of the reasons why pigs are a cost-effective option for farmers is their natural ability to scavenge for food. In some countries in the developing world, pigs are not kept in stables but are allowed to roam freely. This has enabled poor farmers to maintain livestock without vast investments (e.g. infrastructure, foodstuff). Despite its economical benefits, allowing pigs to roam freely increases the rate of transmissions of infectious diseases among pigs and to humans [11].

One infectious disease of particular relevance in the case of free-roaming pigs is Cysticercosis. Cysticercosis is a major cause of epilepsy in the developing world. The disease is caused by a parasite called *Taenia Solium*. The parasite is transferred in a cyclic fashion from pigs to humans through undercooked or raw meat and from humans to pigs through human feces. In rural areas where there is low provision of latrines, people often defecate openly, offering a possibility for pigs to ingest human feces with infective parasite eggs. Cysticercosis is suspected to cause epileptic strokes and death to pigs, as it does to humans.

As a measure against the propagation of infectious diseases in poor African countries, this research aims at gaining understanding into the daily behavior of free-roaming pigs. A previous study used GPS technology to track the movements of free-roaming pigs in western Kenya to gain knowledge about areas visited, distances traveled and amounts of time pigs spent outside their 'home range' [11]. This study found that pigs travel an average distance of more than 4 km in a 12-hour period and spend an average 47% of their time outside their homestead of origin. In addition to tracking the positions visited by pigs daily, the physical activities of pigs could provide relevant information to understand where and how pigs might get infected and even predict the presence of an infection.

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In this paper, we report on the iPig system, an on-going effort to gain knowledge about free-roaming pig behavior. In particular, we have developed a wearable device able to classify free-roaming pig physical activity and a user interface that provides aggregated statistical information about pig's daily behavior to veterinarians. The contribution of this paper is threefold. First, we describe the requirements we elicited for a wearable device for free-roaming pigs. Second, we address the design trade-offs we faced during its development. The requirements we elicited and design decisions we made might prove useful in the development of wearable devices for pigs or other animals. Third, we present the first insights of a study we conducted in order to determine the performance of different supervised machine learning algorithms at classifying pig physical activity.

REQUIREMENTS

In order to elicit the requirements for designing a wearable device to keep track of free-roaming pigs, we conducted a series of interviews with two veterinarians that work with pigs in a daily basis. The first veterinarian performs research in the field of infectious diseases caused by free-roaming pigs in poor regions in Africa. The second one has over ten years experience treating and working with pigs in a stable near Munich, Germany. Based on the interviews, we identified the following requirements:

RQ1 - Safety and welfare. Free-roaming pigs have been reported to walk distances of more than 4 km daily [11]. The design of a wearable device should not limit the pig's ability to walk and scavenge for food or increase its energy expenditure. Furthermore, pigs have a sensitive skin and less hair than most mammals. The wearable device or strap bands should be designed not to cause any injury to pigs' skin.

RQ2 - Robustness. Pigs roll on mud and dirt and are exposed to rain. Furthermore, pigs tend to bite themselves and might try to remove the device as long as they can reach to it with their mouth. Therefore, the wearable device should be water proof, resistant to bites and ideally, be placed at parts of the pig's body where the pig cannot reach it with its mouth.

RQ3 - Low Cost. Free-roaming pigs as well as wearable devices are prone to getting stolen in countries under development. In order to reduce the chances that the device gets stolen and the losses in case it does, the wearable device should have a low cost.

RQ4 - Energy efficiency. Neither farmers or veterinarians might be willing to invest time in removing the wearable devices from every pig in a herd in order to replace or recharge the battery regularly. Therefore, it is critical that the wearable device functions as long as possible without human intervention.

RQ5 - Adaptability. Rapid growth of an animal might cause a strapped wearable device not to fit anymore, cause discomfort and even endanger the animal (e.g. by strangling it when strapped around its neck [3]). Pigs grow on average from 12 kg to 30 kg between their second and fifth month of life [6]. The wearable device should be designed to fit and adapt to the different sizes of a pig.

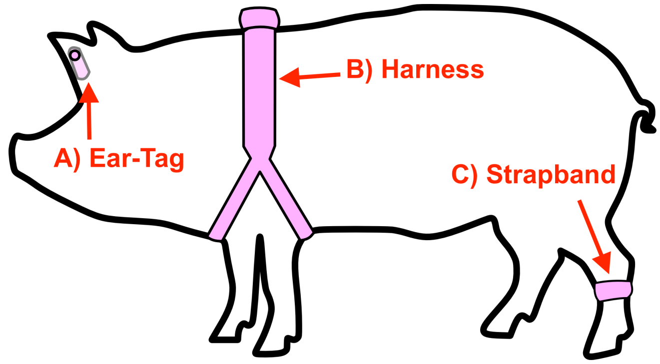

Figure 1. Different designs for a wearable device to be used by pigs.

ANIMAL-CENTERED DESIGN

We designed the wearable device to based on the requirements listed in the previous section and the ethical principles proposed by Mancini [10] with the goal to maximize the welfare of the pigs using the device. We designed the wearable device iteratively by conducting field studies to test our prototypes on different pigs in a stable located in the outskirts of Munich, Germany.

We considered three possible designs for the wearable device: A) an ear-tag, B) a harness fastened around the pig's torso and C) a strap band for the leg. These alternatives are illustrated in Figure 1. We discarded limbs as an alternative to attach a device quickly during the first test, as we observed clear signs of discomfort and lack of acceptance from pigs, which tried to remove the device by biting it. We concluded that pigs would not consent to attach the device to any of their limbs, hence this design would violate the second ethical principle proposed by Mancini: *Garnering participants' mediated and contingent consent* [10]. More importantly, veterinarian suggested that attaching a device to any limb of a pig could cause discomfort and injury to the pig and be easily removed by it.

Alternative B) consisted of a leather harness strapped around the pig's torso. This design had the advantage that it allowed for a bigger device size, hence a larger battery could be placed on it that could last for months. However, during a field test, we observed two major limitations to this design. First, it caused injuries to the pig's skin due to rubbing between the strap band and the pig's skin while walking with the harness attached for a week. Second, the harness would have to be adapted or replaced after a few weeks due to pigs' growth (RQ5). Attaching a wearable device that causes discomfort and injury to an animal would not be acceptable from an animal-centered ethical point of view. Therefore, we decided against this design.

We decided to place the wearable device inside a pig's ear. The device is powered with a knob containing a coin-cell battery that is attached from the outer side of the ear. This design has three main advantages. First, the ear of a pig does not grow in size as much as other parts of its body. As a consequence, a device might remain inserted in a pig's ear for longer periods

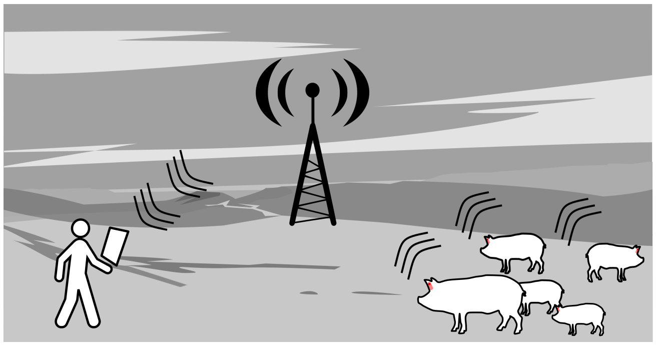

Figure 2. iPig's architecture.

of time (RQ5). Second, the ear cannot be reached by the pig's mouth and is relatively protected from mud and dirt, thus reducing potential damage inflicted upon the device (RQ2). Additionally, the fact that ear tags for pig identification are in use in some commercial farms suggest that the ear has been found to be a convenient place for attachment of electronics by the veterinary medicine community. This also means the practice of punching a wearable device through the ear has been approved by the ethical committees regulating the animal practices in those farms. Attaching a wearable device that causes pain to an animal raises the ethical question as to what extent do its benefits justify the pain and harm involved during the attachment. We argue that our research might improve the life quality of pigs and humans equally by preventing potentially more harmful diseases. An image of a 3D printed casing of the wearable device is shown in Figure 4 (NanoHub).

IPIG

iPig consists of two main components: a wearable device worn by pigs and a user interface on a tablet. The wearable device classifies pig activities based on motion data and sends a daily activity report to the tablet device. The tablet device aggregates the daily activity reports received from different wearable devices and displays statistical information about pig activities and areas where the activities took place. The user interface is shown in Figure 3 and the iPig's architecture is illustrated in Figure 2. In this section, we describe in detail the design of the wearable device and user interface.

Wearable Device

In order to address the strict constrains in terms of size and weight posed by the placement of the device inside a pig's ears, we decided to design a custom motion sensor. We call our wearable device *NanoHub*. The *NanoHub* and contains a 6-axis Inertial Measurement Unit (IMU), an ARM Cortex M0 microcontroller and a Bluetooth Low Energy (BLE) module. In addition, we designed a larger device called *MicroHub*. The *MicroHub* contains an SD card reader and additional electronics to facilitate the software development and testing. We used this device to collect raw motion data from pigs in order to develop our machine learning algorithm. Both devices were designed by Figure 4 shows a comparison of the *MicroHub* and *NanoHub*. Both devices were developed by a company in Munich called InteractiveWear[1].

[1]http://www.interactive-wear.de/

Activity Recognition

One key aspect of the iPig system is knowing what physical activity pigs are doing. Activity recognition based on IMU data has been intensively studied in humans [2, 9]. A few studies have been done on quadrupeds. Cornou et al. have proposed a method based on multi-process Kalman filter to classify pig activities based on acceleration patterns [4]. Ladha et al. [8] developed a wearable device able to detect physical activities linked to the wellbeing of dogs. In cows, several studies investigated physical activity recognition in order to detect lameness [1, 7]. Most of these approaches have used supervised machine learning to classify physical activities.

In another study, Cornou et al. [5] used sensor networks and motion sensors strapped to pig's neck for detecting oestrus based on pigs' acceleration. Furthermore, Thompson et al [12] used IMUs for classifying animals posture (standing, sitting, lateral and sternal lying). None of these studies have focused on pigs roaming in the wild.

Our approach for classifying pig activities consists of three steps:

1. *Preprocessing*. We divide IMU data (linear acceleration and rotation) in windows of 50 samples. We low-pass filter every window using a second order Butterworth low-pass filter at 20 Hz. After applying the filter, we compute the magnitude of each linear acceleration vector. This produces a data set with 7 data points for each time step: linear acceleration and rotation along three axes x,y,z and the magnitude of the linear acceleration. This gives us a matrix of 7x50 values for each window.

2. *Feature Extraction*. For each 7x50 values-window, we compute 5 features: mean, median, standard deviation, Zero Crossing Rate (ZCR) and Peak-to-Peak amplitude (P2P). We selected this set of features based on the fact that they can be implemented on a wearable device at a low computational cost. The feature extraction results in a vector of 35 features which we call "feature vector".

3. *Classification*. We classify the feature vector using a trained machine learning model into one of the following classes: "walking", "eating" or "resting". In the next section, we discuss the classification performance of different machine learning models we studied.

PILOT STUDY

We conducted a study to gain insight into the accuracy of different supervised machine learning models at classifying physical pig activity. This pilot study was realized in a stable in the outskirts of Munich, Germany with the consent of the veterinarian who are legally responsible for the pigs to ensure that to harm was done to the pig during the study.

Setup

We selected a pig randomly from a stable with an outdoor space. The outdoor space contained wild vegetation that enabled pigs to wander and scavenge for food. We attached the sensor to an ear tag worn by the pig and let the pig walk around freely. When the pig stopped walking for too long, we walked

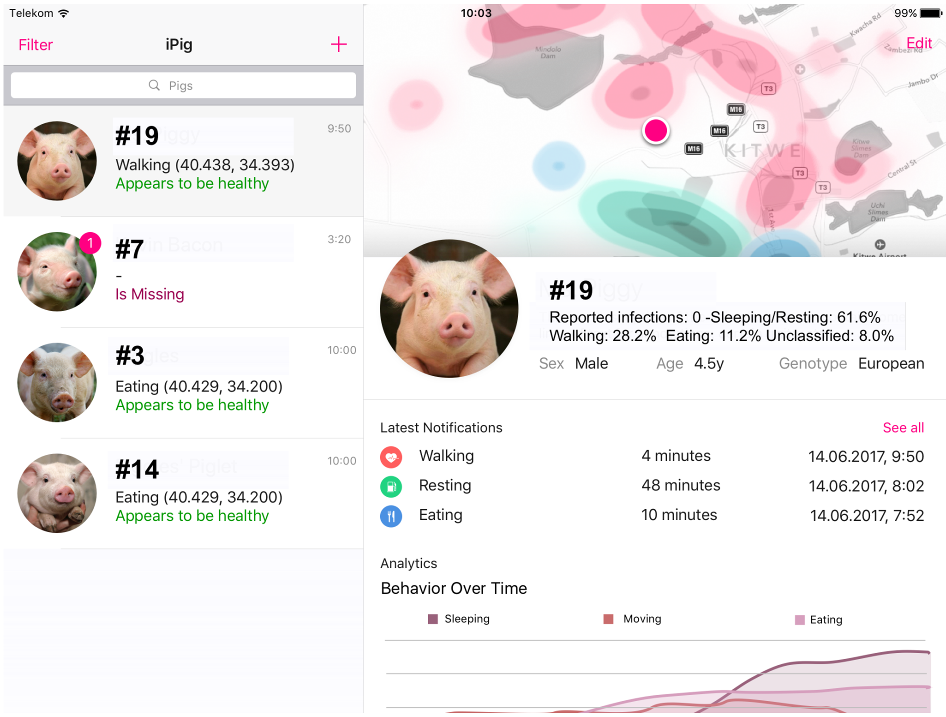

Figure 3. iPig's user interface implemented on an iPad device. On the left side of the interface, a list of pigs is shown, together with it's location and health condition. This enables veterinarians to have an overview of the pigs' health condition and location. One or more pigs can be selected from the list. The right side of the interface displays information about the pig or pigs selected on the left side. The physical activities the selected group of pigs performed in a selectable time range are displayed overlaid on a map of the region at the locations where the activities took place. The activity color mapping goes as follows: walking - red; resting - green; eating - blue. In addition, statistical information about the behavior of the currently selected pigs is shown as a table and timeline.

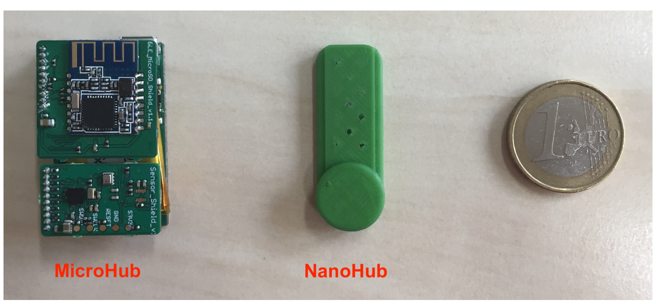

Figure 4. MicroHub (left) and prototype of the NanoHub (middle). Both devices contain a microcontroller, a 6-axis IMU, a BLE module and a battery. However, the MicroHub contains an additional SD card reader needed for development purposes.

behind it to ensure it continued walking and scavenging for food. Figure 5 shows a member of the team walking behind a pig.

We recorded motion data at 100 Hz and videotaped the entire experiment. We then labeled the motion data into periods as: 'walking', 'eating', 'resting' based on the video. We recorded a total of 282s (walking), 8.5s (eating) and 29s (resting). This gave us the following amounts of feature vectors to classify: 1130 (walking), 35 (eating), 118 (resting).

Results

We evaluated the performance of different supervised machine learning models, including Support Vector Machines (SVM), k-Nearest Neighbors (kNN) and linear discriminant. We tried two types of SVM kernels: a cubic and a quadratic kernel and studied the performance of the kNN model with k=1 and k=10 neighbors. Table 1 shows the accuracy, precision and recall of the different machine learning models we studied. The results were validated using the 10-fold cross validation technique. We selected these algorithms based on their public availability.

Figure 5. Image taken during the pilot study with a pig.

Discussion

These results suggest that the wearable device we designed would classify pig activities into walking, eating or resting with an accuracy of 95.8% and a relatively low misprediction rate (precision: 75,4% and recall: 86,6%).

While these results provide first insights into how accurately pig physical activities could be classified using a motion sensor

Table 1. **Performance of different supervised machine learning models at classifying pig physical activity.**

Model	Accuracy	Precision	Recall
SVM (cubic Kernel)	95,87%	75,42%	86,63%
SVM (quadratic Kernel)	95,79%	71,87%	88,46%
KNN (k=1)	94,54%	80,04%	81,16%
KNN (k=10)	95,17%	65,26%	88,16%
Linear Discriminant	94,34%	76,71%	77,14%

attached inside the pig's ear, our experiment has two main limitations. First, the data used to train the model and to validate the model was acquired with the same pig. This could have biased the model to perform well on the pig that participated on the experiment but might perform less accurately when tested with motion data from other pigs. Second, we acquired considerably more data for the "walking" activity. This would cause our model to achieve a high accuracy by favoring the "walking" prediction.

In the future, a larger data set should be acquired for longer periods of time and for several pigs (ideally of different races and sizes). This would produce a larger dataset that could be used to obtain a more generalisable machine learning model. Furthermore, the pigs in the experiment should be let free to perform their natural activities with no human influence in order not to bias their behavior.

CONCLUSION

We have presented an on-going work to enable veterinarians to keep track of free-roaming pigs. In particular, we presented a wearable device able to classify pig physical activities. The results of our pilot study suggest our approach is viable and would even enable the tracking of pig activities with an accuracy of 95.8%. However, a longer-term in-field deployment of the iPig system is necessary to determine the performance of our approach under a more unconstrained setting and would serve for identification of issues with respect to the requirements we elicited.

We assessed different designs for the wearable device and decided for a design meant to be inserted inside a pig's ear. The fact that pigs in many commercial farms already use ear tags opens up a possibility for our wearable device to be integrated in the ear at almost no added cost. Keeping track of pigs' physical activities could be useful to monitor and better address the needs of pigs in stables as well (e.g. predict disease and pregnancy).

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