Title: Evaluation of the Kinect v2 motion-sensing camera to develop a rapid and effective tool for identifying compromised pigs. – **NPB #16-122**

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Industry Summary:

Ensuring the health and wellbeing of pigs is of the utmost importance to the swine industry. However, one of the biggest challenges to ensure the health and wellbeing of pigs is the rapid and accurate identification of compromised (injured or illness) pigs. However, to date, the only method utilized to identify compromised pigs is visual recognition. While effective, there is substantial room for improvement/enhancement. A major limitation to visual identification is that the pig must exhibiting visual indicators that can be recognized by the producer. Thus, until the pig is displaying recognizable behavior/movement there is no intervention. As such, there is a need for a real-time system that can identify changes in pig activities, as well as activity patterns to accurately identify compromised pigs prior to observance of visible clinical symptoms by facility personnel during daily checks. Therefore, a novel computer vision system that can automatically maintain individual identification and continuously track activities of group housed pigs was developed and evaluated. Thus, the objective of this research trial was to evaluate the viability of the depth-sensing camera coupled with multi-ellipsoid fitting and deep learning detection programing to automatically identify, maintain identity and continuously track the activities of group housed newly weaned nursery pigs. To accomplish this objective, three trials were conducted within a commercial nursery (~1,300 head, Union Farms, Ulysses NE) and one trial within the Animal Science Complex at the University of Nebraska – Lincoln. For each trial, the system was installed above a pen with 14 – 15 newly weaned nursery pigs. At the conclusion of each trial, captured data was analyzed to evaluate the system's ability to identify, maintain identity, and track the activities/activity patterns of activity of the nursery pigs. Evaluation of 1,020 randomly selected data points indicated an 99.8% accuracy rate for correctly identifying pigs' location within the pen, body orientation and identity of the pig when standing/walking. Orientation/identity accuracy was reduced to 92.5% when pigs were lying. Classification accuracy for activities was 99.1, 93.6, 97.3, and 80.0% for lying, standing/walking, at the feeder and at the waterer, respectively. The accuracy of the system provides the ability to accurately track the activities of group housed nursery pigs and evaluate changes in these activities over time. Utilizing data, we were able to evaluate the time spent associated with each activity. Activity data generated from the trial conducted at the Animal Science Complex indicated that during the first 15 d of the nursery phase, pigs spent 78.3% of time lying, 17.5% of time standing/walking, 6.5% of time at the feeder, and 0.6% of time at the waterer. The average time associated with each activity also changed over time. On the first day of the nursery phase, pigs spent 72% of the time lying. By day 15, time lying had increased to 81%. On average, pigs traveled 11.3 miles (59,893 feet) during the first 15 days of the nursery turn. The average daily distance traveled was 3,989 ft / day; ranging from 2,874 to 4,718 ft./day. As the time pigs spent in the nursery phase, the distance traveled each day decreased. During the first 5 days, the average distance traveled was 0.90 miles (4744 ft). During the last five days (days 11 – 15), the average distance traveled was 0.67 miles (3526 ft). In addition, the system is capable of functioning in the unique environmental conditions of a commercial nursery facility. Across the trials conducted, the system continuously collected data for 60 days within a nursery facility with no technical failures. Overall, the results of this study indicate that the system (depth-sensing camera coupled with multi-ellipsoid fitting and deep learning detection programing) is capable of accurately for identify individual pigs, maintain identity of these pigs within a nursery pen. The system is also capable of accurately tracking the activities of multiple pigs over an extended period of time within the environmental conditions of commercial nursery facility.

Keywords:

Real-Time Tracking, Computer Vision, Depth-Sensing, Pig Daily Activity, Nursery Phase.

Scientific Abstract:

Ensuring the health and wellbeing of pigs is of the utmost importance to the swine industry. As such, there is a need for a real-time system that can identify changes in pig activities, as well as activity patterns to accurately identify compromised pigs prior to observance of visible clinical symptoms by facility personnel during daily checks. Therefore, a novel computer vision system (depth-sensing camera coupled with multi-ellipsoid fitting and deep learning detection) which automatically identifies, maintains identity and continuously tracks the activities of group housed pigs was evaluated. Within a commercial nursery, the system was installed over a single pen with 15 newly weaned pigs (24 d of age) and continuously collected data upon introduction of pigs for a period of 4 d. Within the Animal Science Complex at the University of Nebraska – Lincoln (UNL), 28 newly weaned pigs (21 d of age) were stratified by gender/litter and randomly assigned to one of two mixed gender pens. The system was installed over each pen and continuously collected data for 15 d. Evaluation of 1,020 randomly selected frames indicated an 99.8% accuracy rate for correctly identifying pigs' location, body orientation and identity when classified by the system as standing/walking. When classified as lying, orientation/identity accuracy was reduced to 92.5%. Classification accuracy for activities was 99.1, 93.6, 97.3, and 80.0% for lying, standing/walking, at the feeder and at the waterer, respectively. Activity data generated from the UNL trial indicated that during the first 15 d of the nursery phase, the average time spent 78.3, 17.5, 6.5, and 0.6% of time lying, standing/walking, at the feeder, or at the waterer, respectively. Average daily distance traveled was 1,213.6 m (range: 876 - 1,438 m). Results indicated that time associated with each activity changed over time ($P \leq 0.001$). On d 15, time lying and time at the feeder were greater ($P \leq 0.001$) than d 1 (8.0 and 6.0%, respectively). Time standing/walking and time at the waterer were less on d 15, when compared to d 1 (9.6 and 0.7%, respectively). Gender had no effect ($P \geq 0.25$) on time lying, walking, at the feeder, or total distance traveled. Gilts spent less (P = 0.007) time standing and more (P = 0.03) time at the waterer than barrows. Results suggest that the novel computer vision system has the capability and sensitivity to accurately identify, maintain identification, and track the activities of group housed nursery pigs.

Introduction:

Ensuring the wellbeing and growth-rate efficiency of livestock is a fundamental challenge facing the agriculture industry, particularly as increasing demand for products and small profit margins force operations to scale up. To date, the only method used by producers to analyze animal health and well-being is traditional manual observation. Because this method requires the animals to display obvious signs of injury, illness, stress, or inefficiency, there is substantial room for improvement and enhancement, especially in how quickly compromised/injured animals are identified and treated. In modern swine facilities that house several thousand pigs, it is a daunting task to ensure that each pig is visually inspected even so much as once each day. Thus, intervention is often delayed until recognizable symptoms are presented.

Enhancing both the speed and accuracy of the identification process presents a significant step toward improving the overall wellbeing and efficiency of pigs through preventative treatment options and enhanced management practices. Treatment of morbid pigs prior to systemic infection could drastically improve effectiveness of therapeutic treatment, management of injured pigs, reduce or potentially eliminate the need for low dose antibiotics, reduce disease load of the herd, and provide insight to potential pathogen outbreaks. Rapid identification of injured pigs could allow producers to identify and address issues before the injury becomes detrimental to the pig's wellbeing by preventing further tissue damage. In addition, a system with the capabilities to monitor aggressive pigs that are inflicting tail or ear biting (or are territorial to feed and water access) could be a significant tool for implementing management practices to reduce the impact on pen mates and to isolate the culprit.

A 1% change in mortality rates in swine wean to finish systems has a production cost associated with it of $0.42 per head. On a national level, that 1% change equates to over $47 million per year. For systems that must market pigs on a fixed timeline, a delay in identifying an issue that slows pig growth even by as little as one pound per pig takes 82.9 million pounds of pork out of the system and reduces potential income of US swine farmers by $67.2 million. Timely and accurate intervention is easily a multi-million-dollar solution.

Objective:

Within a commercial nursery facility, conduct a two-part experiment to evaluate the Kinect v2's ability to maintain identification, track movement, and delineate normal behavior of pigs.

Image 1: Kinect v2 mounted to the ceiling looking down on the pen

Materials and Methods:

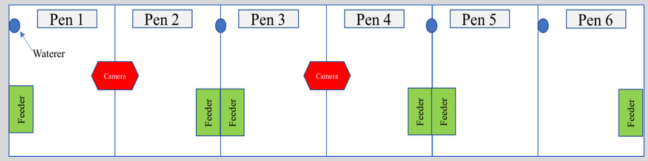
To evaluate the ability of the system [high definition depth-sensing camera (Kinect v2 camera, Microsoft®) and a mini CPU (NUC, Intel®)], two separate studies were conducted. The first study was conducted at a commercial nursery facility (Union Farms) in Ulysses, NE. The second study was conducted within the Animal Science Complex at the University of Nebraska – Lincoln (UNL).

Figure 2. Methods for identification of individual pigs

Within the commercial nursery facility, the system was installed and evaluated during three nursery turns. Objective was to collected video data for a period of 24, 48, and 72 hours, respectively. Twenty-four hours prior to the start of each turn, the system was installed above a single pen (figure 1) and programed to start the capture of video images upon placement of the pigs within the assigned pen.

At the time of arrival, 15 newly weaned pigs (single gender) were randomly selected and assigned to the pen. Prior to placement into the pen, body weight, heart girth, flank girth, and body length were recorded and each pig was provided an individual identification marker. To maintain identification, three systems were evaluated; paint-brands, livestock spray paint bar pattern, and visual ear tags (figure 2). Following placement, the system began the collection of continuous collection of video images. At the conclusion of each nursery turn, body weight and body measurements were collected and video data downloaded for analysis.

Figure 3. Schematic of nursery room utilized for turn conducted at UNL



A similar protocol with some modifications was utilized for the nursery trial conducted at the University of Nebraska – Lincoln’s Animal Science complex. Utilizing 28 newly weaned mixed gender nursery pigs and were stratified by body weight, liter, and gender and randomly assigned to two nursery pens (pen 1 and pen 3; figure 3). Visual ear tags were utilized for maintaining identification and video data were collected for 56 continuous days. Body weight and body measurements were recorded on days, 1, 3, 10, 16, 23, 30, 37, 44, and 56. On day 28, seven randomly selected pigs from pen 1 were moved to pen 2 and seven pigs from pen 3 were moved to pen 4 to ensure adequate pen space/pig.

Figure 4. Image of camera placement and changes in camera placement for cover two pens

Camera view days 1 - 27 Camera view days 28 - 56

For collection of data, two independent systems were installed in the nursery. Each system was situated above the respective pens to allow for collection of data from both pens. Days 1 thru 27, systems were angled to collect data from a single pen (1 and 3, figure 4). On day 28, angle of cameras was adjusted to capture data from both pens (1/2 and 3/4, figure 4). On day 14, 28, 32, and 56, hard drives were downloaded and analyzed.

Results:

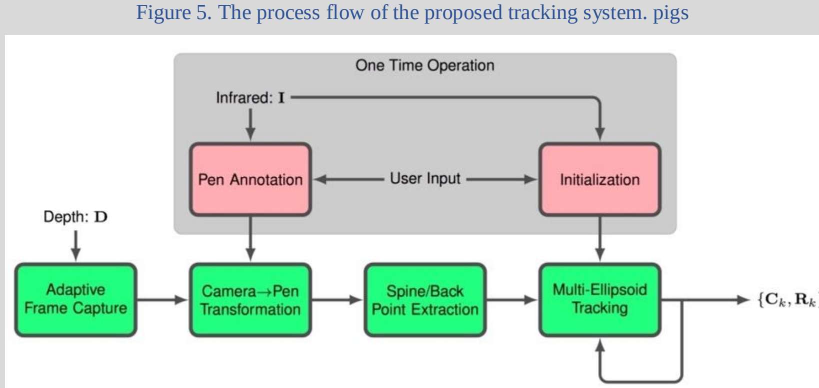
Duration of data capture (Objective 1): Electrical issues related to the nursery facility prematurely terminated the capture of data for the first and second turn. Five hours after the start of the first nursery turn, lightning struck the barn, disrupting power and shutting the system down. During the second turn, powered was disrupted due to a blown fuse, shutting down the system after 22 hours. From the first two turns, a total of 27.3 hours of video was captured and analyzed. While both turns were prematurely terminated due to electrical issues associated with the nursery facility, data generated allowed for enhancement of the system and creation of a preliminary tracking system. Identification using both paint brands and stripped paint patterns were determined to be ineffective at maintaining identity. Furthermore, a significant amount of hard drive storage space was occupied by frames collected during times of inactivity.

Utilizing results of the first two turns, modifications were made to rate of frame capture (adaptive-frame rate capture program created), identification of individual pigs (visual ear tags), and use of independent back-up power source. Based upon results of modifications to the system, the goal for the third turn was to continuously capture data for the entire nursery turn (56 days). Modifications significantly improved the capabilities of the system and a total of 4 days (132 hours) of video was captured. Similar to the first two turns, electrical issues associated with the nursery facility prematurely terminated the capture of data (failure of the electrical outlet). While the 4 days was significantly less than anticipated, this was almost one-fold greater than proposed for objective 1.

Duration of data capture (Objective 2): Shifting the trial to the Animal Science Complex at the University of Nebraska – Lincoln drastically improved the ability to capture data for objective 2. The data was captured for the entire 56 days (1,344 hours) of the nursery phase with no interruption. With no complications associated with capture of data, pigs and systems were moved to the grower pens and data was captured for an additional 80 days.

Creation of tracking methodology: Uutilizing the data from the three nursery turns, a tracking method was created utilizing output of the depth-sensing camera to track multiple pigs simultaneously in a group housed environment. Figure 5., illustrates the flow of data through the various stages of processing. The user is required to annotate the pen only once assuming the camera does not move with respect to the pen environment (figure 6). Before tracking begins, the position of the pigs is also initialized by the user.

Figure 5. The process flow of the proposed tracking system. pigs

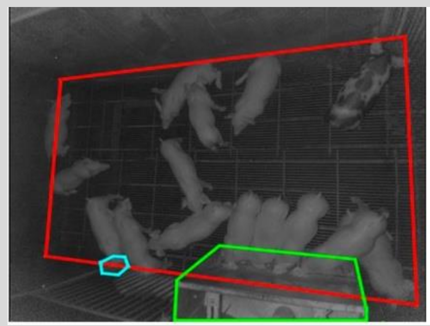


The process begins with an adaptive frame capture method designed to minimize the amount of data necessary to perform multi-object tracking. Then, using a set of one-time initializations from the user, a series of operations are performed on the depth data to achieve the position Ck and orientation Rk of each pig k in the pen

The process of movement and activity tracking can be divided into the following five stages:

1. Adaptive rate capture of depth images
2. One-time pen annotation
3. Spine/back point extraction
4. Multi-ellipsoid expectation maximization
5. Motion filtering using adaptive exponential smoothing

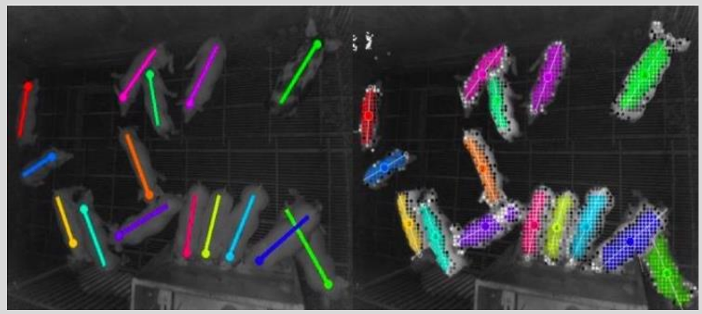
Figure 6. User selected regions corresponding to the pen floor (red boundary), the feeder (green boundary, and waterer *cyan boundary)



During times of inactivity, the positions of targets remains constant and processing new frames wastes computational resources. Therefore, an adaptive-rate frame capture method was developed to reduce the computational workload without sacrificing target tracking accuracy. This method effectively senses movement in the environment and reacts by capturing new data. After data has been captured, the user performs a one-time pen annotation by selecting the pen boundaries, feeder, and waterer. The process, illustrated in figure 6, is critical for separating the foreground points belonging to pigs from background points in the scene. It is also used to establish the height of the pigs, and their movements; both of which are necessary for tracking activities. After applying the manual annotation, 3D foreground isolation is used to remove all points that belong to the static environment. Because the camera is only capable of capturing a one-sided depth map of each pig, tracking operates by fitting an ellipsoid to the viewable surface of the pigs; here, their spine/back surface. Given a collection of spine/back points, an ellipsoid tracker is used to maintain the position and orientation of each pig. It operates by enforcing shape consistency between frames while allowing small movements. For each frame captured, the ellipsoid tracker adjusts the position of an ellipsoid to each new set of spine/back points. The operation is similar in nature to the k-means algorithm and generally falls into the category of hard expectation maximization (EM). In the context of EM, the proposed method alternates between an expectation step when assigning maximum-likelihood (minimum distance) clusters to points via a metric enforcing ellipsoidal shape, and a maximization step when recalculating parameters of the clusters. Finally, adaptive exponential smoothing is used to filter the motion of each target, where the movement of occluded pigs restricted to prevent unwanted drifting.

To evaluate the proposed multi-object tracker, a continuous sequence of 2,100,000 frames was captured over a 5- day period at Union Farms in Ulysses, Nebraska. Color, infrared, and depth frames were captured using a downward-facing Microsoft Kinect v2 camera mounted 2.1 meters above a 1.5 x 2.5 meter pen that contained 15 pigs. It is worth noting that, despite the harsh environmental conditions of the commercial swine facility, the system ran continuously without interruption during the entire duration of the trial. Whereas multi-object trackers are typically evaluated using bounding box overlaps with manually annotated frames, this approach is unsuitable for evaluating the performance of the proposed 3D tracker. This is because tracking results largely adhere to a binary state: either perfect overlap or a well-defined tracking error. In addition, bounding box overlap metrics do not consider the orientation of the targets, which is important for identifying the activities of pigs. Instead, evaluation is performed by initializing the positions of all 15 pigs at a starting frame and letting the tracker proceed until an error is observed. A total of 30 starting points were randomly chosen from the dataset, and the positions of the pigs was initialized manually as shown in Figure 7. It should be noted that frames where one or more pigs is mostly occluded were not used for initialization. This is because manual selection cannot be reliably performed by the user if the pigs are not sufficiently visible in the image. Three distinct types of tracking errors were observed during the trails: orientation flips, lost tracks, and label swaps. During an orientation flip, the head moves to the position of the tail and vice versa. The second type of error is a lost track, where the centroid of the ellipsoid moves far enough away from the intended cluster of points that there is no longer any overlap. Finally, the third type of error, referred to as swap labels, is when the ellipsoids from more than one pig are shuffled and no longer match their original targets. During label swaps, each pig has an ellipsoid tracking its movements, but two or

Figure 7. The image on the left illustrates the user-defined initialization of the pigs' heads and tails. These points are used to initialize the multi-ellipsoid tracking, where the membership of each subsampled point is illustrated by the colored points in the image on the right



more of the identities is incorrect. Table 1 presents the results of each manually initialized tracking session. On average, the tracker maintains the position and orientation of all pigs for 2767 consecutive frames, or 592.2 seconds before encountering a single error. Assuming symmetry between forward and backward tracking, an average of 5534 frames or 1184.4 seconds should exist between tracking errors. In contrast, when the motion filtering described in section 3.5 is removed, the tracker only maintains tracks for an average of 613 frames. This is a 4.5x increase in the duration of reliability that can be attributed to motion filtering. It should be noted that a common cause of failure without motion filtering resulted from lost depth data due to flies walking in front of the depth camera. In terms of the types of errors, a total of six, 12, and 12 errors could be attributed to orientation flips, lost tracks, and swapped labels, respectively. In many cases, orientation flips could be corrected with additional processing. For example, by tracking the direction of movement and forcing this direction to be in the forward direction. Lost tracks could likely be corrected by using per-frame detection and looking for targets with no assigned labels. The last, and most challenging type of error is swapped labels. To correct for swapped labels, it would be necessary for the tracker to distinguish between targets using some form of fingerprinting. While conventional methods of target fingerprinting may not be suitable to homogeneous populations of animals, recent work has demonstrated that it is possible to extract subtle features from an animal's appearance. Preliminary results suggest that the system is capable of accurately

Figure 8. Point cloud accumulation for physical dimension estimation along with width estimates of ilium, flank, shoulder, and neck (top). Weight estimated, as a function of the distance between the neck and ilium and flank width, is approximately 0.3 kg

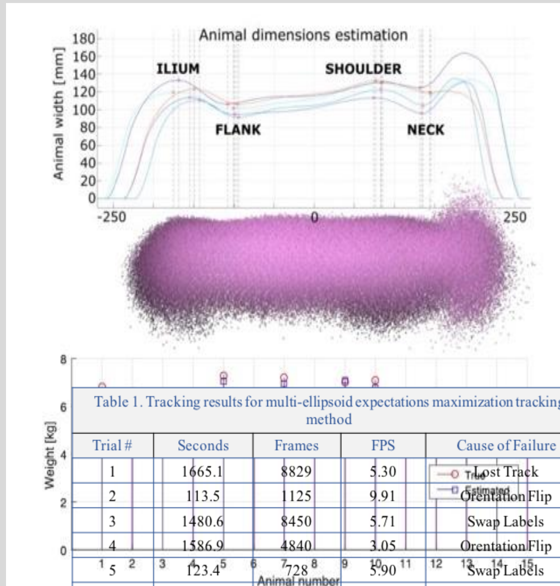


Table 1. Tracking results for multi-ellipsoid expectations maximization tracking method

Trial #	Seconds	Frames	FPS	Cause of Failure
1	1665.1	8829	5.30	Lost Track
2	113.5	1125	9.91	Orentation Flip
3	1480.6	8450	5.71	Swap Labels
4	1586.9	4840	3.05	Orentation Flip
5	123.4	728	5.90	Swap Labels
6	325.3	2878	8.85	Orentation Flip
7	16.6	151	9.10	Orentation Flip
8	116.0	1373	11.84	Lost Track
9	8.0	62	7.75	Swap Labels
10	188.0	1407	7.48	Lost Track
11	188.0	898	4.78	Orentation Flip
12	1140.9	4686	4.11	Swap Labels
13	1440.8	7440	5.16	Lost Track
14	514.7	3400	6.61	Lost Track
15	1200.0	2510	2.09	Lost Track
16	28.2	302	10.71	Swap Labels
17	234.8	990	4.22	Lost Track
18	144.5	581	4.02	Swap Labels
19	10.8	152	14.07	Lost Track
20	101.8	966	9.49	Lost Track
21	1089.7	3527	3.23	Lost Track
22	87.1	727	8.35	Lost Track
23	394.1	1479	3.75	Swap Labels
24	1408.8	9843	6.99	Swap Labels
25	859.7	2195	2.55	Swap Labels
26	169.1	1890	11.17	Lost Track
27	46.3	417	9.01	Orentation Flip
28	1292.5	5622	4.35	Swap Labels
29	255.1	2653	10.40	Swap Labels
30	1536.6	2877	1.87	Swap Labels
AVE	592.2	2767	6.73	

characterizing/parameterizing the pigs. By gathering data collected by the system over long durations, we could extract the top-down side contours shown in Figure 8 (top). To illustrate the system's ability to accurately parameterize pigs, the manually recorded weight of each pig and the weight predicted from the data are presented in Fig. 6 (bottom). An empirically derived using second and first order terms relating the measurements to weights is given by:

$$Weight = 0.0002 \times FlankWidth^2 + 0.0413 \times NeckToIlium - 8.0739,$$

Lengths are in millimeters and weight is in kilograms.

The mean absolute error between the manually measured weight and the predicted weight is 0.3kg.

Visual Identification using Deep Learning:

After experimenting with a variety of visual marker techniques, we have found ear tags to be the most reliable solution to the visual identification problem. The solution that we are currently using relies on a combination of colors and numbers that make it easy for an observer to identify specific pigs from a video feed. Figure 9 shows a sample of three tags that were used for identification. For the preliminary results, we used blue, green, red, yellow, and white with the numbers 1, 22, and 333 for a total of 15 combinations. In addition to providing a method for manual identification, the tags were also used for automated detection. Specifically, we developed a two-stage deep learning framework for automated detection and classification of tags from video frames. The first stage consists of an R-CNN stage that identifies the locations of each tag in the images. The second stage consists of a network that classifies the tags into one of the 15 types. It is worth noting that detection and classification could be joined into the same fully convolutional neural network to significantly speed up processing. Preliminary results, shown in figure 10 demonstrate the accuracy of deep learning for

Figure 9. Visual tags used by system for animal identification

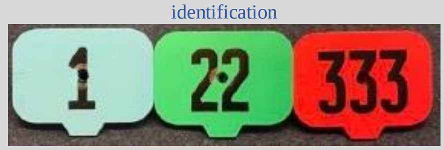


Figure 10. Sample from illustrating the results of deep learning

tag detection. When combined with the multi-ellipsoid tracker, the system was able to automate continuous localization and detection of basic activities for the entire duration of the trial. The combination effectively operates by automatically resolving label swaps, orientation flips, and lost tracks whenever a tag is identified with very high probability. To evaluate the accuracy, we randomly sampled the annotated video at 68 points and compared the observed localization and activity detection to the system's results. The results given in Table 2 demonstrated that, when standing/walking, the pigs' locations, orientations, and identities are detected with 99.8% accuracy. When lying down, the accuracy drops to 92.5% accuracy.

Table 2. Number of errors observed in 68 randomly sampled frames with 1020 detections. Each error is separated into two categories: 1) errors that occur when the pig is standing (included walking, eating, and drinking) and 2) errors that occur when the pig is lying

	Label Swap	Label Swap	Orientation Flip	Orientation Flip	Lost Track	Lost Track
Occurrences	0	36	1	16	1	24

Table. 3. Confusion table illustrating the accuracy of manual observation vs. automated detection. A total of 68 and 1020 activities were observed.

Observed/Detected	Lying	Standing/Walking	Eating	Drinking
Lying	660	6	0	0
Standing/Walking	2	175	5	5
Eating	0	4	143	0
Drinking	0	4	0	16

The difficulty of tracking pigs that are lying down is due to the tendency to be occluded by other pigs that might be lying on top of them or stepping over them. In terms of activity detection, the results in Table 3 demonstrate that, when the pig was lying down, their activity was correctly identified 99.1% of the time. When eating, this activity was detected with 97.3% accuracy, while drinking events were correctly identified 80.0% of the time. Errors associated with drinking event detections are likely due to the small area designated to the drinking cup and the relative inaccuracy of the head localization.

Incorperation of tracking method to evalaute activity of newly weaned pig: Utilizing the tracking alogithum and deep learning framework, data captured from the 3rd nursery turn from the commercial facility and the UNL nursery turn. Data was segregated into five specific activities: lying, standing, walking, eating and drinking (figure 11). For eating and drinking activitie, activitie is classified based upon proximately to the feedeer or waterer (no indication of food or water intake). Activity data generated from the 3rd commercial facility is reported in table 4 and activity data for nursery turn within nursery facility at UNL is reported in table 5.

Figure 11. Determination of activities based up location within the pen and body orientation in relation to the pen and the depth-sensing camera

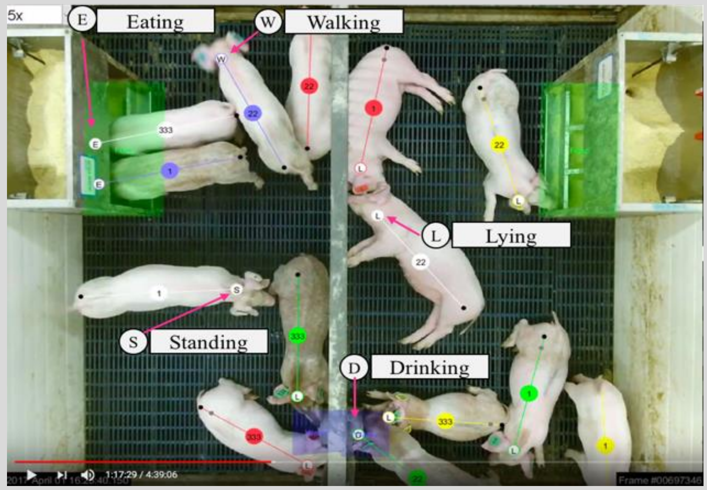


Table. 4. Individual and pen average activity data collected during the first 4 days of the nursery phase within a commercial nursery facility.

ID	% Time during first 4 days				Distance
	Lying	Stand/Walk	Eating	Drinking	Traveled (meters)
B1	74.1	15.0	9.7	1.2	9,491.5
B22	58.3	23.7	16.9	1.1	13,610.8
B333	75.6	12.2	10.5	1.6	9,427.1
G1	66.0	19.3	13.3	1.3	12,174.1
G22	65.5	15.6	17.1	1.8	11,966.4
G333	68.7	16.4	13.8	1.1	11,370.9
R1	68.1	15.0	15.9	1.0	11,484.1
R22	69.1	17.0	12.8	1.1	11,205.2
R333	71.9	16.0	10.8	1.2	9,560.7
W1	69.5	18.5	11.3	0.8	11,481.0
W22	70.9	18.5	8.9	1.7	11,184.1
W333	70.3	16.9	11.2	1.5	12,226.8
Y1	73.9	15.1	9.5	1.4	8,827.1
Y22	62.5	23.9	12.4	1.1	15,345.1
Y333	71.8	13.7	12.9	1.5	10,764.4
Pen	Lying	Stand/Walk	Eating	Drinking	Distance
AVE	69.1	17.1	12.5	1.3	11,341.3
Min	58.3	12.2	8.9	0.8	8827.1
Max	75.6	23.9	17.1	1.8	15,345

Discussion:

Results of this study indicate that the use of a depth-sensing camera coupled with multi-ellipsoid fitting and deep learning detection programing is able to accurately identify, maintain identity and continuously track the activities of group housed newly weaned nursery pigs. The current system was capable of identifying, maintaining identification, and track the activities of group housed newly weaned pigs for an extended period of time. Ability of the system to continuously maintain identification and track activities significantly exceeded expectations. For objective 1, a stair-step approach was planned to achieve a desired data capture duration of 3 days. We were able to exceed this proposed duration and capture data for 4 complete days. While this was only 24 hours more than proposed, results provided evidence that the system was highly capable of capturing data for an extended duration (electrical issues related to the commercial facility prematurely terminated all three turns). Shifting the trials for objective 2 to the nursery facility UNL provided a more stable power source and allowed us to fully evaluate the systems' capabilities. Within the UNL nursery facility, the system was able to capture data for a period of 136 days. Data was captured for the entire 56 days of the nursery phase and 80 days of the grower/finisher phase. Due to enormous amount of data collected (148 TB) and time required for development of the multi-ellipsoid fitting and deep learning detection programing, we currently have only been able to analyze and report the activity data from the first 15 days of the nursery turn at UNL. Furthermore, system hard ware was capable of functioning within the unique environmental conditions of the nursery facility. Both the depth-sensing cameras and NUC mini computers were able continuously function for 136 days with no required maintenance.

Table. 5. Individual and pen average activity data collected during the first 15 days of the nursery phase within a nursery facility at UNL.

ID	% Time during first 15 days				Distance Traveled (meters
	Lying	Stand/Walk	Eating	Drinking	
Pen 1 (UNL)					
B1	76.2	15.1	11.3	0.2	16,155.0
B22	80.2	16.6	5.6	0.5	15,770.8
G1	78.1	18.4	6.1	0.2	15,770.8
G22	76.2	19.9	6.4	0.3	15,770.8
G333	78.0	17.9	6.7	0.2	17,814.8
R1	76.2	19.5	6.8	0.3	17,280.8
R22	80.0	16.0	6.6	0.2	18,862.6
R333	79.7	17.2	5.5	0.5	17,723.2
W1	76.3	19.8	6.3	0.4	21,572.8
W22	75.7	17.6	9.2	0.3	17,185.3
W333	77.5	15.9	9.3	0.1	16,909.6
Y1	77.5	19.7	5.4	0.2	20,800.3
Y22	79.1	16.9	6.6	0.2	18,444.4
Y333	76.0	18.1	8.4	0.3	19,980.1
AVE	77.6	17.8	7.2	0.3	18,306.1
Min	75.7	15.1	5.4	0.1	15,770.8
Max	80.2	19.9	11.3	0.5	21,572.8
Pen 3 (UNL)					
B1	80.8	15.5	5.9	0.7	17,121.4
B22	81.7	13.9	6.4	0.8	13,142.3
G1	79.2	16.1	6.6	0.9	17,015.6
G22	78.2	17.8	6.0	0.9	19,034.1

G333	78.1	18.5	5.6	0.6	19,059.0
R1	79.1	18.2	4.9	0.6	19,305.7
R22	78.5	16.1	7.4	0.8	19,161.8
R333	75.1	20.6	6.3	0.9	21,147.2
W1	79.4	17.3	5.2	1.0	18,427.5
W22	79.4	18.2	4.3	1.0	20,375.7
W333	77.8	18.6	5.4	1.0	18,547.4
Y1	76.8	18.8	6.4	0.8	19,907.5
Y22	78.1	16.8	6.8	1.2	18,208.5
Y333	82.9	16.0	3.3	0.6	14,414.6
AVE	78.9	17.3	5.7	0.9	18,204.9
Min	75.1	13.9	3.3	0.6	13,142.3
Max	82.9	20.6	7.4	1.2	21,147.2

The systems accuracy rate for identification (99.8%) and tracking activities (92.5%) exceeded our initial expectations and continued analysis of data and enhancement in deep learning training will only increase the accuracy. This rate of accuracy is extremely vital in our ability to achieve a primary goal of utilizing the system to accurately identify pigs exhibiting clinical symptoms related to illness/injury prior to observation during daily barn checks. In addition, we hypothesize that the system may be able to accurately identify and track more sophisticated activities/behaviors such as belly nosing (figure 12), aggression at the feeder (figure 13), aggression, and tail biting. The ability to accurately identify immune compromised or injured pigs prior to human observation would be a significant benefit for the industry, not only in terms of production efficiency, but also enhancement of the treatment and overall wellbeing of pigs.

The accuracy of the system has allowed for the initial evaluation of the system's ability to accurately predict changes in body weight. While the we currently only have preliminary data from the 4 day commercial nursery turn, results suggest an ability to utilize the systems as a means of predicting changes in body weight and possibly body composition. The ability to predict body weight without the need for a physical scale could provide the swine industry with a significant tool for the management of pigs during the grower/finisher phase. Possibly providing producers with an accurate method for identification of harvest ready individuals, drastically reducing the error associated with human observation.

Overall, the system is capable, accurate, durable, and not cost prohibitive (depth-sensing camera coupled with coupled with multi-ellipsoid fitting and deep learning detection), thus possibly may serve as a significant tool for the swine industry and a tool for the academic community. Further evaluation is still needed, with a primary focus on the processing and management of data. In addition, the current data is limited in our abilities to make statistical inferences related to the activities of pigs and changes in activities of pigs experiencing various stressors, challenges and situations within the production phases.

Figure 12. Image of individual (Yellow 22) repeatedly identified as belly nosing pen mate (Blue 22)

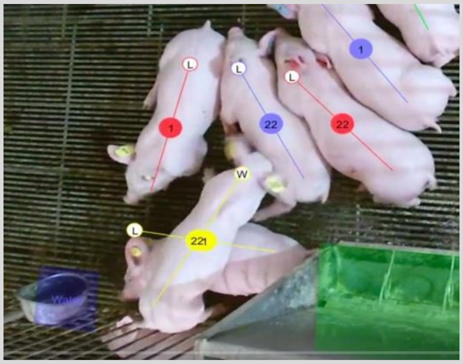


Figure 13. Aggression at the feeder instigated by Yellow 1 when approached by White 333