Pig Health Abnormality Detection Based on Behavior Patterns in Activity Periods using Deep Learning

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***Abstract*—Abnormal detection of pig behaviors in pig farms is important for monitoring pig health and welfare. Pigs with health problems often have behavioral abnormalities. Observing pig behaviors can help detect pig health problems and take early treatment to prevent disease from spreading. This paper proposes a method using deep learning for automatically monitoring and detecting abnormalities in pig behaviors from cameras in pig farms based on pig behavior patterns comparison in activity periods. The approach consists of a pipeline of methods, including individual pig detection and localization, pig tracking, and behavioral abnormality analysis. From pig behaviors measured during the detection and tracking process, the behavior patterns of healthy pigs in different activity periods of the day, such as resting, eating, and playing periods, were built. Behavioral abnormalities can be detected if pigs behave differently from the normal patterns in the same activity period. The experiments showed that pig behavior patterns built in 30-minute time duration can help detect behavioral abnormalities with over 90% accuracy when applying the activity period-based approach.**

Keywords—Deep learning; pig tracking; behavior patterns; pig health monitoring

I. Introduction

Pig tracking plays an important role in the early detection of problems in pig health and welfare. Traditionally, this job is done by workers on pig farms. This manual method has a number of disadvantages. Firstly, workers cannot monitor all pigs continuously and all the time, because they have many other jobs to do. Secondly, they lack the capability to remember and associate the behaviors of each individual pig over a long period of time to detect behavioral abnormalities. In addition, on large pig farms, this task requires a lot of labor.

Tracking pigs automatically not only reduces labor costs, but can also provide better performance since pig behaviors can be observed and associated over a longer period of time. By recording pig behavior measurements over a long period of time, the changes in behavior patterns of pigs can be detected, and these can be used as early signs of disease. If the decision can be made only at the observing time and can not be associated with other observations in the past, only serious clinical signs can be detected, which may result in a late intervention [1].

Pig tracking can be performed in groups or at the individual level. Although group behavior measurement has been proven to have usefulness in pig health and welfare monitoring, individual behavior detection and tracking has more advantages as it can enable personalized abnormal detection and treatment [1]. Obviously, tracking individual pigs is a more challenging task than tracking group of pigs because of the potential errors in individual pig detection and identification. Recently, with improvements in object detection and tracking techniques, pig tracking has been focused on individual-level.

Tracking pigs from surveillance cameras is a widely used method due to its low cost and simplicity of installation when compared to wearable methods. Depth sensors such as 3D cameras have been used to measure the depth of pig images detected to identify if a pig is standing or lying [2, 3, 4, 5], but this kind of device is expensive, and this method cannot be used to identify other postures such as eating or drinking. Recently, deep learning approaches have been utilized to detect, track, and identify exact behaviors of individual pigs. Based on the convolutional neural network (CNN) architecture, a number of multi-object detection algorithms have been introduced, such as Faster R-CNN [6], SSD [7], YOLO [8]. These algorithms can help locate and classify objects in images, which can be used for pig localization and posture classification in video frames from surveillance cameras. This approach worked on inexpensive 2D RGB cameras and has the ability to identify various pig behaviors such as standing, lying, eating, drinking, foraging, etc. [4, 5, 9, 10, 11, 12, 13, 14] or identify moving, non-moving behaviors [1]. Non-moving behaviors can be identified in the detection phase by dividing pig classes of the detection model into sub-classes such as pig standing, pig lying, pig eating, etc. [1, 10, 11] or using an additional image classification model to classify the detected pig images into different behavior classes [13]. Moving behaviors, such as walking or running, can be identified in the tracking process by measuring the distance that a pig traveled between continuous frames [1, 13]. In addition to basic postures and behaviors, some researchers tried to identify more complex postures, such as sitting, lateral lying, sternal lying, etc. [11]. When the behaviors can be identified during the tracking process, changes in pig behaviors can be detected by considering the time for each behavior [10, 13] or time spent moving, being idle, and distance traveled [1].

One of the most challenging issues in pig tracking is identification errors caused by identity switching or changing problems during the multi-object tracking process. Some previous works have tried to improve this problem by using additional methods, such as a correlation filter-based tracker via a novel hierarchical data association algorithm [15] or trajectory processing and data association [16]. However, due to the natural conditions of commercial pig farms, such as high pig density, low light, similar appearances of pigs, or wide covering area of cameras, tracking each individual pig for a long time with low identification error rate is still a difficult task.

In this paper, we propose a pipeline of methods, including detection, tracking, building healthy pig behavior patterns, and behavior abnormality detection based on comparison of new pig behaviors and healthy pig behavior patterns. We tried to reduce the impact of identification errors by calculating the behavior patterns in 30-minute-long videos. Moreover, to make the behavior patterns built in only a 30-minute time duration but still have capabilities for detecting behavioral abnormalities, we built different behavior patterns for each activity period in a day. According to our studies, pigs have typical behaviors during different activity periods in a day, such as resting time, eating time, playing time, and building different behavior patterns for each activity period can improve the behavioral abnormality detection performance.

In our method, videos from cameras installed on pig pens will be streamed to the Yolo v7 model [17] to detect pig locations and postures. In the detection phase, pigs detected will also be classified into different posture classes, such as standing, lying, and eating. Pig locations in continuous video frames will be used to identify the individual pigs and track their movements using the DeepSORT algorithm [18]. While lying and eating behaviors are identified in the detection phase, standing and moving behaviors need to be determined in the tracking phase. In the tracking phase, we can measure the distance between the locations of each individual pig in continuous frames. If the distance between locations of a pig is less than a threshold number in some continuous frames, the pig can be determined to be idle rather than moving. Based on the behaviors recognized in the detection and tracking processes, behavior patterns can be built for different activity periods of a day. The experiments showed that the behavior patterns, which were built from 30-minute time duration, could reduce the identification error but still show behavioral characteristics in each activity period.

The main contributions of our method are:

- Proposed an end-to-end method for detecting and, tracking pigs individually, measuring their behaviors and building behavior patterns, detecting behavioral abnormalities.
- Proposed an approach for building healthy pig behavior patterns in different periods of time in a day, such as rest time, eating time, and playing time. With this approach, we can build behavior patterns in only 30 minutes to reduce the identification error. Based on the behavior patterns, abnormalities can be detected by calculating the difference between the tracked pig behavior set and the behavior patterns. We tested our approach on both healthy and sick pig datasets.

The rest of the paper will be structured into the following sections. Section II describes the materials and methods for pig detection, tracking, and behavior analysis. Section III describes the experiments and results. Section IV finalizes a conclusion.

II. Materials and Methods

A. Datasets

The datasets used in this paper were collected from two pens on a commercial pig farm. One pen (Pen 1) contains healthy pigs, and the other one (Pen 2) contains sick pigs (which were collected from other pens for quarantine purposes). Videos from both pens were used to create the pig detection and tracking datasets. Videos from Pen 1 were used to build healthy pig behavior patterns, and videos from Pen 1 and Pen 2 were used to build test datasets for behavioral abnormality detection.

The video was recorded using one EZVIZ (resolution: 1920 x 1080, focal length: 4.0mm, max frame rate: 15 FPS) on pens containing 15-18 pigs with ages from 3 months to 4 months and weights from 40 kg to 50 kg.

The videos were recorded across different days and times to collect the data in different conditions. Fig. 1 shows the sample images from the experimental pens.

Fig. 1. Sample images from experimental pens.

From this raw dataset, we created pig detection, pig tracking, pig re-identification, and pig behavior analysis datasets for our experiments. The details of these datasets are described in the next sections.

1) Detection dataset: To create the detection dataset, we extracted image frames from captured videos and manually annotated them using the LabelImg tool [19]. Using this tool, we created a bounding box for each pig in the images and assigned it one of three classes: standing, lying, or eating (to annotate the eating behavior, we need to create a bounding box covering not only the pig but also the feeder as well, so that the model can learn if it is eating food in the feeder trough or not).

Totally, 3.069 images were extracted from recorded videos and annotated for training and testing the detection model (48.522 annotations). The images were extracted from videos captured at different times in order to test the detection and tracking performance in various illumination and weather conditions.

2) Tracking dataset: To create the detection dataset, we just need to create a bounding box for each pig and assign it a behavior class, as mentioned above. But to create the tracking dataset, we need to assign each pig the same identification number (ID) from frame to frame.

The frames in the tracking dataset are selected in the order they appear in the video but don't need to be continuous because the frame rate of videos is very high. On average, we just selected and annotated one-fourth of the frames on each testing video. To test the tracking performance of both pens, we create two tracking subsets on videos from Pen 1 and Pen 2, as described in Table I. As mentioned above, the frames in a tracking subset must be put in order, so it can be seen as a sequence of frames.

TABLE I. SUMMARY OF TRACKING DATASET

	Sequence Length (seconds)	Number of frames
Sequence from Pen 1	300	247
Sequence from Pen 2	300	250

3) Pig re-identification dataset: The pig re-identification dataset contains individual pig images for the purpose of recognizing the individual pig without consideration for its behaviors. Therefore, it includes all the pig images in the pig behavior dataset plus other pig images we collected by using the detection model. Totally, we obtained 5.460 images for 30 pig identities for our pig re-identification dataset.

4) Pig behavior analysis dataset: This dataset includes 30-minute videos collected from both pens to build behavior patterns and test abnormaltity detection based on behavioral analysis. In particular, the dataset consists of the following videos:

- Nine videos collected from the healthy pig pen in three activity periods, as mentioned above. Three videos were collected randomly in each activity period to build the behavior pattern for that period.
- Three videos collected from the healthy pig pen in three activity periods for testing purposes.
- Three videos collected from the sick pig pen in three activity periods for testing purposes.

B. Method

In order to build the behavior patterns of pigs in a video, they first need to be detected in each video frame. The detections obtained in continuous video frames are used for tracking the pigs and identifying their behaviors. In our method, the detections can be used to identify non-moving behaviors such as lying, standing, or eating with corresponding class labels. However, to determine the moving behavior, we need to consider the distance between pig locations in continuous frames during the tracking process.

Fig. 2 shows the overall architecture of our system. The methods applied in each module are described in the following sections.

1) Pig detection: In this phase, the YOLO v7 model was used to detect the pigs. The YOLO is a popular object detection algorithm and is widely used today due to its speed and accuracy. It is a single-state object detection scheme that divides images into a grid, in which each cell in the grid is responsible for detecting objects itself.

YOLO v7 is an object detection architecture entirely written in Pytorch with models pretrained on the COCO [20] dataset. We chose to use YOLO v7 because it is significantly faster and more accurate compared to the previous versions. We first pre-trained the model with the COCO dataset, and followed by our own dataset as a fine-tuning task. The pre-training step is necessary when training most CNNs for image classification or detection to obtain good initial weights on an extremely large dataset (millions of images).

In the following stage, we fine-tuned the model using our detection dataset. The purpose of the model is not only to detect the pigs but also to identify non-moving pig behaviors such as standing, lying, and eating.

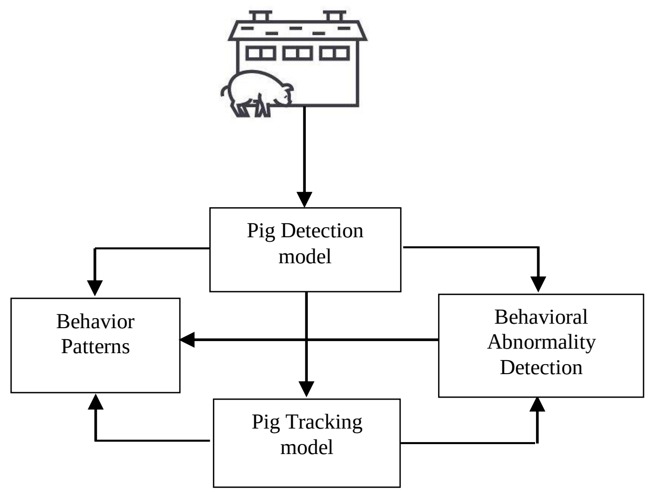

Fig. 2. Overall architecture of our method and system.

2) Pig tracking: From the locations of pigs detected in the frames, we employed DeepSORT, a multi-object tracking (MOT) technique, to track the pigs in videos. DeepSORT uses the Kalman filter [21] to track the objects detected in the frames in the previous step (using one of the object detection algorithms such as YOLO, R-CNN family, etc.). The Hungarian algorithm [22] will be used to match the tracked objects and detections in the next frame. DeepSORT not only uses the distance between tracks and detections as measurements of matching but also uses deep image similarity as an additional metric. This greatly reduces the number of misidentified objects and can help re-identify the objects that have not been tracked in the previous frame (in the pig tracking task, this can be caused by the bad illumination conditions). To measure the image similarity, we used the OSNet (Omni-Scale Network) [23] model, pre-trained on the person re-identification dataset and followed by our own pig re-identification dataset.

The original DeepSORT was developed for a general multi-object tracking context in which the number of targets is unknown. When applying it to the group-housed pig tracking task where the number of pigs is stable, DeepSORT can assign a different ID to the same pig target as the video frames grow and the pig goes far from camera or changes the behavior. This will cause the identification switch errors and increase the ID beyond the real pig's numbers, making the behavior extraction task for individual pigs not stable. To solve this problem, we employed the improved DeepSORT algorithm proposed by S. Tu et al. [16], in which we added an additional re-matching step for lost and new tracks using both trajectory and data association processing. This remarkably improves the tracking performance and reduce the identification errors as described in the tracking results section.

3) Behavioral abnormality analysis: In this phase, we used the results of the detection and tracking phases to determine the behaviors of each individual pig. In particular, if the posture of a pig recognized in the detection phase is lying or eating, its behavior is determined to be the same. If the posture of a pig recognized in the detection phase is standing, the change in its position in the tracking phase (if any) will be used to determine if it is standing or moving. We set a threshold for the distance between positions of the pig in continuous frames. If the distance is greater than the threshold, the pig is determined to be moving; otherwise it is standing.

Based on that scheme, all four behaviors of pigs will be identified during the detection and tracking phases. From the behaviors identified in the frame sequences, the total amount of time for each behavior will be calculated over a period of time to build the behavior patterns of pigs in each activity period. In this research, we introduce the term "activity period", which implies a period of time in a day that the pigs mainly perform some typical behaviors. In our experiment, we set the time for each activity period as in Table II. Please note that the times for activity periods may vary on different farms. But in commercial settings, farm owners can set the times for them, and system can collect data and build the behavior patterns accordingly.

TABLE II. TIME FOR ACTIVITY PERIODS

Activity Periods	Time	Description
Resting period	0h-7h, 8h-10h, 14h-16h, 18h-24h	Pigs mostly spend time for resting, sleeping
Eating period	7h-8h, 13h-14h, 17h-18h	Pigs mostly spend time for eating
Playing period	6h-7h, 16-17h	Pigs mostly spend time for playing, looking for food

We chose the time duration to build behavior patterns is 30 minutes and the behavior patterns will be calculated for three activity periods in a day, as mentioned above. The 30-minute time duration was chosen to balance the identification errors and the abnormality detection abilities of behavioral patterns. If the time duration is shorter, identification errors can be reduced, but the behavior patterns may not be sufficient to represent the activity periods. While a longer time duration may produce a better behavior pattern, identification errors will increase. Since the current farm's natural conditions do not guarantee accurate long-term tracking, a 30-minute time duration for building behavior patterns is a reasonable choice.

The healthy pig behavior patterns in each activity period will be calculated as follows:

- Calculating the time for each behavior of each individual pig in each 30 minutes.
- Building the behavior patterns of healthy pigs by averaging the time for each behavior in the same activity period.
- Building the daily behavior patterns of healthy pigs by averaging the 30-minute behavior patterns in the same activity period.
- Behavior patterns will be calculated for three activity periods, as mentioned above.

Behavior patterns will be built and updated on a daily basis. The behaviors of tracked pigs will be calculated using the same formula and compared to the behavior patterns. The difference between them will be calculated using the Euclidean distance, and a threshold will be set for abnormality detection.

During the tracking process, some tracks may be lost and reappear, and their behaviors will not be recorded during that time. To make the behavior patterns and extracted behavior set have a consistent time, we assign the behaviors in lost time according to the previous and subsequent behaviors (half of time for the previous and half of time for the subsequent). Therefore, the total time for all behaviors in behavior patterns and behavior sets is always 30 minutes.

III. RESULTS AND DISCUSSION

A. Evaluation Metric

1) Detection evaluation: To evaluate the performance of the detection model, we used the mAP (mean Average Precision) metric, which is a standard metric to evaluate the performance of most common object detection methods. We first compute the IoU of the ground-truth bounding boxes with detected boxes as in Eq. (1).

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \quad (1)$$

From the IoU metric of each bounding box pair, we computed the AP (Average Precision) metric for each class, and mAP is the mean of all APs as in Eq. (2) and (3).

$$AP(c) = \frac{TP(c)}{TP(c)+FP(c)} \quad (2)$$

$$mAP = \frac{1}{classes}\sum_{classes} AP(c) \quad (3)$$

Where *TP(c)*, *FP(c)* are True Positive, False Positive, respectively and *AP(c)* is the AP score of class *c*.

2) Tracking evaluation: The tracking performance metric used in our experiments is MOTA (Multi-Object Tracking Accuracy) [24]. This metric is calculated based on three types of errors: FN (False Negative), FP (False Positive), and IDSW (Identity Switch) as in Eq. (4).

$$MOTA = 1 - \frac{\sum_i FN_i + FP_i + IDSW_i}{\sum_i GT_i} \quad (4)$$

Where FN_i is a real object but the tracker for it was not generated, FP_i is a non-existing object in ground truth but the tracker for it was generated wrongly, $IDSW_i$ is a mismatch, and GT_i is ground truth.

We also used *IDF1* as a second metric to evaluate the tracking model. This metric focuses on the identity switch, which evaluates the ability to track identities.

$$IDF_1 = \frac{2IDTP}{2IDTP+IDFP+IDFN} \quad (5)$$

Where *IDTP*, *IDFP*, *IDFN* are True Positive, False Positive, False Negative on identity switches.

3) Behavioral abnormality detection evaluation: Each pig tracked will be assigned a unique identification (ID) with four behavior metrics, which are the time for each behavior in 30 minutes. These metrics will be compared to the behavior pattern in the same activity period using Euclidean distance as in Eq. (6).

$$d(Y,\hat{Y}) = \sqrt{\sum_{i=1}^{n}\left(Yi - \hat{Y}i\right)^2} \quad (6)$$

Where Y is the behavior pattern and $\hat{Y}$ is the behavior set of the tracked pig.

If the distance is greater than the threshold number, a behavioral abnormality is detected. In the testing process, if an abnormality is detected in a sick pig, the prediction is correct, and vice versa. The performance of behavioral abnormality detection can be evaluated by dividing the number of correct predictions by the total prediction number (Accuracy score).

B. Detection Results

The results of the detection phase are shown in Table III. Please note that besides mAP, we also reported the Precision and Recall scores for the detection model.

TABLE III. RESULTS OF PIG DETECTION MODEL

Class	mAP	Precision (%)	Recall (%)
Stand	99.3	98.3	98.5
Lie	99.6	98.6	99.1
Eat	98.9	97.0	97.0
All	99.3	97.9	98.2

The reported detection results are very good in all metrics, considering the natural conditions of the commercial pig farm in our dataset. The cameras do not have a good viewing angle due to the low ceiling of pens, which was designed for human monitoring and also for saving purposes. For this reason, some pigs are overlapped in videos when they stay close to each other and far from the camera. If pens are designed to support the automatic tracking task with a higher ceiling, the detection results will be better. Fig. 3 shows a case where a pig was hidden by the feeder due to the low camera viewing angle and could not be detected.

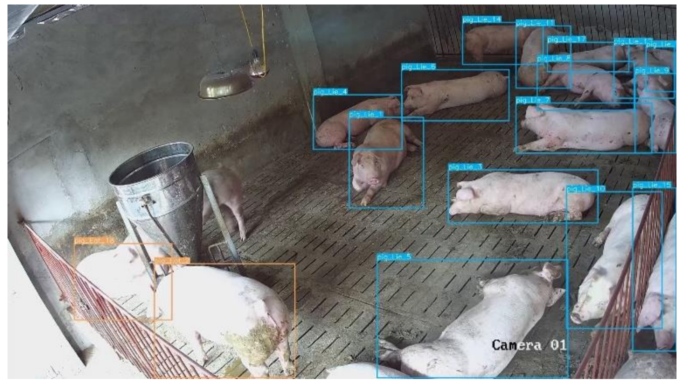

Fig. 3. Sample image for a detection errors when a pig was hidden by the feeder due to the low camera viewing angle.

C. Tracking Results

Table IV shows the results of the tracking model in MOTA and IDF1 scores. We also reported the number of identity switches (IDS), which calculates the times when trackers swap from one to another. This metric is also important because it shows the number of identification errors during the tracking process.

TABLE IV. RESULTS OF PIG TRACKING MODEL

Validation set	Original DeepSORT			Improved DeepSORT		
	MOTA (%)	IDF1 (%)	IDS	MOTA (%)	IDF1 (%)	IDS
Sequence 1	91.5	93.4	13	92.8	95.6	10
Sequence 2	92.5	94.0	10	94.3	96.1	8
Avg.	92.0	93.7	11.5	93.6	95.9	9

The overall MOTA (93.6 %) and IDF1 (95.9 %) are satisfactory. Results for Sequence 2 are slightly higher because it was collected from the sick pig pen, where pigs move less than in the healthy pig pen.

The average number of IDS is 9, meaning that each pig changed its identification only about 0.4 times on average during the tracking process. In our object tracking algorithm, the objects are tracked not only based on their trajectory but also on their visual similarity. And the object in the current frame will be associated with the object in some frames before it. Therefore, even though the pigs in the previous frames and the current frame are predicted to have different class labels, they will be assigned the same ID. This is important for the tracking process because it will not cause identification errors.

Fig. 4 illustrates the cases where pigs change behaviors during the tracking process but their IDs remain unchanged.

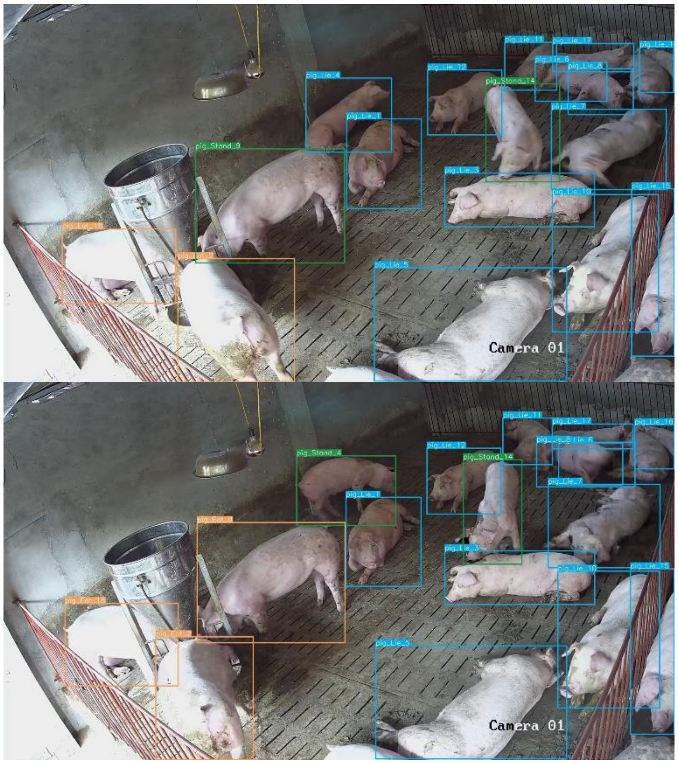

Fig. 4. Sample frames for tracking results when pig 9 was approaching the feeder with the recognized behavior "Standing" (above), then changed to "Eating' (below), but the ID was not changed. Similarly, the pig 4 changed behavior from "Lying" to "Stangding" but the ID is the same.

D. *Behavioral Abnormality Detection Results*

Based on the pig behavior analysis datasets, the experimental process of behavior analysis and abnormality detection is as follows:

- Building healthy pig behavior patterns: Nine videos from the healthy pig pen for behavior pattern building purposes are fed through the detection and tracking models. The time for behaviors of individual pigs in these videos is calculated and averaged to build three behavior patterns of healthy pigs in three activity periods in a day. Please note that in commercial settings, the behavior patterns can be built using more 30-minute videos collected from tracking cameras. We just used three videos for each activity period for experiment purposes.

- Testing on the videos collected for testing purposes: Six videos from the healthy pig pen and sick pig pen (two for each activity period) are fed through the detection and tracking models. The behavior of each individual pig will be calculated and compared to the healthy pig behavior pattern in the same period built in the previous step using the Euclidean distance formula.

Table V shows the healthy pig behavior patterns built from videos.

TABLE V. HEALTHY PIG BEHAVIOR PATTERNS

Activity period	Moving Time	Standing Time	Lying Time	Eating Time	Total
Resting	0.4	0.4	29.2	0	30
Eating	5.3	5.2	0.5	19.0	30
Playing	23.1	4.5	1.8	0.5	30

From the behavior patterns shown in the above table, we can see the typical behaviors of healthy pigs during each activity period of a day. For example, in the resting period, pigs spend most of their time lying while in the playing time, they mostly move around the pen (for playing or searching for food).

Table VI shows the time of each behavior for each pig in testing videos and the Euclidean distance between each pig behavior set and the healthy pig behavior pattern in the same activity period.

TABLE VI. BEHAVIOR TIME FOR PIGS IN TESTING VIDEOS

A) RESULTS ON A HEALTHY PIG VIDEO IN THE RESTING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	0	0	30	0	0.9
2	0	0	30	0	0.9
3	0	1	29	0	0.8
4	0	0	30	0	0.9
5	0.5	1	28.5	0	1.0
6	1	1	28	0	1.5
7	0	0	30	0	0.9
8	1.5	2	26.5	0	3.4
9	0	0	30	0	0.9
10	0	0	30	0	0.9
11	0	0	30	0	0.9
12	1	1	28	0	1.5
13	0	0	30	0	0.9
14	2	3	25	0	5.2
15	0	0	30	0	0.9
16	1	2	27	0	2.8

B) RESULTS ON A SICK PIG VIDEO IN THE RESTING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	0	0	30	0	0.9
2	0	0	30	0	0.9
3	0	0	30	0	0.9
4	0	0	30	0	0.9
5	0	0	30	0	0.9
6	0	0	30	0	0.9
7	0.5	0	29.5	0	0.5
8	0	0	30	0	0.9
9	0	0	30	0	0.9
10	0.5	0	29.5	0	0.5
11	0	0	30	0	0.9
12	0	0	30	0	0.9
13	0	0	30	0	0.9
14	0	0	30	0	0.9
15	0	0	30	0	0.9

C) RESULTS ON A HEALTHY PIG VIDEO IN THE EATING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	4.5	5.5	0	20	1.4
2	5	2	1.5	21.5	4.2
3	5	12	0	13	9.1
4	2	12.5	0	15.5	8.7
5	2	4	2	22	4.8
6	2.5	2	0	25.5	7.8
7	1.5	4	0	24.5	6.8
8	4.5	8.5	0	17	3.9
9	5.5	6	0	18.5	1.1
10	4	12	0	14	8.5
11	4.5	4	0	21.5	2.9
12	3	2	0	25	7.2
13	2	5.5	0	22.5	4.8
14	5	5	0	20	1.2
15	3	2.5	0	24.5	6.6
16	5	3	0	22	1.9

D) RESULTS ON A SICK PIG VIDEO IN THE EATING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	1.0	0.5	15.5	13.0	17.4
2	1.0	1.8	25.8	1.3	31.4
3	2.0	2.7	23.3	2.0	28.8
4	3.3	2.0	8.7	16.0	9.5
5	2.3	5.8	10.5	11.3	13.0
6	4.0	5.0	7.0	14.0	8.3
7	2.8	5.5	8.7	13.0	10.4
8	1.5	4.3	6.8	17.3	7.6
9	0.8	3.7	12.8	12.7	14.6
10	4.3	4.7	10.0	11.0	12.5
11	5.0	9.0	15.0	1.0	23.4
12	3.2	3.2	8.3	15.3	9.1
13	2.2	1.0	12.2	14.7	13.5
14	3.7	5.3	10.0	11.0	12.5
15	2.0	2.9	23.5	1.6	29.1

E) RESULTS ON A HEALTHY PIG VIDEO IN THE PLAYING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	15	14	0	1	12.6
2	25	5	0	0	2.7
3	22.5	5.5	0	2	2.6
4	24.5	3.5	2	0	1.8
5	26	4	0	0	3.5
6	20	8.5	0	1.5	5.4
7	21	7.5	1.5	0	3.7
8	20	7	3	0	4.2
9	21	6	0	3	4.0
10	20.5	9.5	0	0	5.9
11	17.5	10.5	0	2	8.5
12	20	9.5	0.5	0	6.0
13	22	7.5	0	0.5	3.7
14	21	4.5	4.5	0	3.4
15	20	8.5	1.5	0	5.1
16	19	9	0	2	6.5

F) RESULTS ON A SICK PIG VIDEO IN THE PLAYING PERIOD

Pig ID	Running Time	Standing Time	Lying Time	Eating Time	Euclidean Distance
1	8.8	7.3	13.8	0.0	18.9
2	5.7	6.3	18.0	0.0	23.8
3	7.7	4.8	17.5	1.7	22.0
4	7.0	11.3	11.7	0.0	20.1
5	8.3	8.0	13.7	0.0	19.2
6	4.0	9.7	17.0	0.0	24.9
7	12.2	5.0	12.3	0.5	15.2
8	13.7	4.0	12.3	2.3	14.2
9	12.3	4.7	12.7	0.3	15.3
10	6.3	9.7	14.0	0.0	21.3
11	7.0	10.0	13.0	0.0	20.3
12	4.2	6.2	19.7	0.0	26.1
13	8.0	9.0	13.0	0.0	19.3
14	15.0	5.5	9.5	0.0	11.2
15	8.8	7.3	13.8	0.0	18.9

As shown in Tables VI(A) and VI(B), pigs spend almost all of their time lying in both healthy and sick pig videos in resting period. Therefore, it is difficult to detect behavioral abnormalities in this period. We may only detect the pigs infected with a disease that makes them excited and move or run continuously, even in the resting period. However, there is no pig with that kind of disease in our datasets, so we cannot draw conclusions about that case.

The detection of behavioral abnormalities is much better in the two remaining activity periods. Results from Tables VI(C) and VI(D) showed that the healthy pigs spent most of their time eating, but the sick pigs also spent a considerable amount of time lying during the eating period. Therefore, if we set a threshold for Euclidean distance to 9, we can detect behavioral abnormalities with accuracy around 90% on average (15/16 are correct predictions for healthy pigs and 12/14 are correct predictions for sick pigs). Similarly, if we set the Euclidean distance threshold to 12 in the playing period, the accuracy on average is around 93% (15/16 correct predictions for healthy pigs and 14/15 correct predictions for sick pigs).

In our experiments, due to the regulations in the livestock sector, we had difficulties infecting the healthy pigs with the viruses to make them sick. Instead, we used the sick pigs collected from other pens to collect data for testing. Therefore, the pigs in sick pig videos are different from the pigs in healthy pig videos, which are used to build behavior patterns. The abnormality detection performance for sick pigs will be better if behavior patterns are built on the same pigs that are tracked. This is feasible in commercial settings, in which behavior patterns are built in the same pen with tracked pigs (abnormality detection for pigs today can use the behavior patterns built yesterday).

IV. Conclusion

We proposed a method for pig behavior detection, tracking, and behavioral abnormality analysis based on behavior patterns built from 30-minute videos in different activity periods under the natural conditions of pig farms using deep learning. We conducted various experiments to illustrate our method on our own datasets collected from a commercial pig farm, including healthy pig and sick pig datasets.

The experiment results showed that the behavior patterns built using the activity period-based approach can capture the typical characteristics of pigs in each activity period and can be used to detect behavioral abnormalities in pigs.

The activity period-based approach also has a lot of potential for future improvements. For example, more activity periods can be studied and used rather than only three, or weights can be assigned for behavior metrics to indicate the importance of typical behaviors in each activity period. We can also add more metrics to the behavior patterns and develop a more sophisticated method for abnormality detection based on the behavior patterns.

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