Novel tracking method for the drinking behavior trajectory of pigs

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Abstract: Identifying and tracking the drinking behavior of pigs is of great significance for welfare feeding and piggery management. Research on pigs' drinking behavior not only needs to indicate whether the snout is in contact with the water fountain, but it also needs to establish whether the pig is drinking water and for how long. To solve target loss and identification errors, a novel method for tracking the drinking behavior of pigs based on L-K Pyramid Optical Flow (L-K OPT), Kernelized Correlation Filters (KCF), and DeepLabCut (DLC) was proposed. First, the feature model of the drinking behavior of a sow was established by L-K OPT. In addition, the water flow vector was used to determine whether the animal drank water and to demonstrate the details of the movements. Then, on the basis of the improved KCF, the relocation model of the sow's snout was established to resolve the problem of tracking loss in the snout. Finally, the tracking model of piglets' drinking behavior was established by DLC to build the mapping association between the pig's snout and the drinking fountain. By using 200 episodes of drinking water videos (30-60 s each) to verify the method proposed in this study, the results are explained that 1) according to the two important drinking water indexes, the Down (−135°, −45°) direction feature and the V2 (>10 pixels) speed feature, the drinking time could be accurate to the frame level, with an error within 30 frames; 2) The overlapping precision (OP) was 95%, the center location error (CLE) was 3 pixels, and the speed was 300 fps, which were all superior to other traditional algorithms; 3) The optimal learning rate was 0.005, and the loss value was 0.0 002. The method proposed in this study realized accurate and automatic monitoring of the drinking behavior of pigs, which could provide reference for other animal behavior monitoring.

Keywords: tracking method, drinking behavior trajectory, pigs, L-K optical flow, KCF, DeepLabCut
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1 Introduction

The drinking behavior of pigs is an important indicator of animal welfare feeding and health status[1]. The presence of diseases, poor feeding quality, or changes in the environment may affect drinking behavior[2]. The problem of drinking water quantity has been solved by predecessors with sensor equipment[3,4]. However, the identification of the drinking behavior of pigs in groups is still accomplished through manual monitoring and invasive electronic identification equipment[5]. Given the influence of complex backgrounds, such as pig occlusion, fast movement, and illumination, traditional algorithms have difficulty achieving long-term target tracking[6], not to mention the challenge of conducting refined research on accurately locating the pig snout and the water fountain. Therefore, the study of an efficient and real-time non-contact identification method for the drinking behavior of pigs in a group can obtain information on patterns and alert the abnormal state of pigs, which is conducive to improving their growth welfare[7-9].

Research on drinking behavior tracking mainly includes two steps: 1) The target tracking of the drinking area (snout and drinking fountain) and 2) the identification of the drinking behavior (contact and duration). In terms of target tracking, several machine vision methods are used to solve the tracking efficiency, such as the filtering method[10], the optical flow method[11], the kernel function[12], trackers[13], and the deep learning model[14]. In addition, numerous positioning studies have been conducted on the different parts of pigs, including the head, tail, center of mass, and contour[15]. However, given the influence of occlusion and adhesion, the tracking target is often lost, thus being unable to locate the pig's snout and the water fountain. In terms of behavior recognition, machine learning methods are often used to identify different behaviors, such as illness, fighting, eating, and drinking water[16-20]. In recent years, as a feature description tool, the optical flow method[21,22] has been used to study the behavior of livestock and poultry[23]. Optical flow estimation can collect behavioral features and physiological parameters, which is a convenient method for extracting the snout features and water flow features of pigs' drinking behavior. However, the tracking accuracy and speed are not high due to the great influence of the environment. Kernelized Correlation Filters (KCFs)[24] are often used for video target tracking, which is a technique with a stable effect on the trackers.

Aiming at the problem of target tracking loss in the snout of sows, it can assist the optical flow method to form the target relocation of pigs' drinking behavior. With the advantages of the robust model and a small number of labeled samples, DeepLabCut (DLC)[25] is often used for the pose estimation of experimental

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animals (mice, fruit flies, etc.) under high-definition video, which can make up for the deficiency of KCFs in tracking the drinking behavior of the piglets[26,27]. Therefore, this research can feasibly examine the feature extraction, target tracking, and trajectory visualization of pigs' drinking behavior on the basis of these three technologies. The main problems to be solved are 1) the lack of spatial and temporal features of drinking behavior, 2) the continuous tracking of the snout and water fountain, and 3) the redundancy and drift of drinking behavior trajectory.

In this study, a novel feature-extracting and target-tracking method was introduced, named L-K OPT-KCF-DLC, to overcome the above issues. In summary, the main contributions of this research are as follows:

1) The optical flow analysis of water movement was carried out on the basis of the L-K pyramid optical flow (L-K OPT) method. In addition, the Gaussian pyramid was used to optimize the feature dimension. Then, the optical flow field was used to supplement the time, the velocity, and the direction vector of the space-time dimension;

2) KCF based on block sampling was used to optimize the speed. In addition, the eight-neighborhood idea was adopted to expand the sampling block to realize the repositioning of the snout between frames;

3) A trajectory tracking model based on DLC was proposed, which realized the depth tracking of the piglets in the snout and water fountain and improved the problems of trajectory loss and drift.

2 Materials and methods

2.1 Subject and environment

The video collection date was from May 2019 to November 2019. The collection location included large-scale farms in Qingdao, Shandong Province, China. The pig species were Yorkshire of different ages. The video scene is shown in Figure 1.

Figure 1 Video capture scene

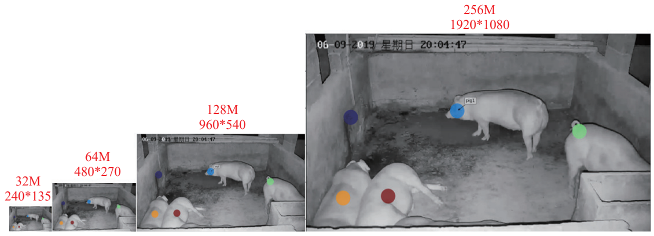
In this work, OpenCV3.4.9 (Platform for Visual Studio2015) and PyCharm were selected as programming tools to realize the video tracking experiment of drinking behavior. The desktop computer was configured as Intel(R) Core(TM) i7-7700 CPU @ 3.60 GHz×8, 16 GB DDR, Ubuntu 18.04.2 (64 bit). Nearly 200 videos (24 h) were collected in sunny, cloudy, wet, and dry environments, respectively.

2.2 Data label and data set

A pig retreating or bowing its head, which caused its snout to leave the water fountain, was defined as the end of the drinking period; any other action was defined as a new episode. The drinking interaction action was taken as the truth value by artificial markers.

First, as shown in Figure 2, the video size was normalized from 1920×1080 pixels to 960×540 pixels, 480×270 pixels, and 240×135 pixels to verify the efficiency and accuracy at different magnitudes. Second, the key videos were intercepted to reduce the amount of data training. The processing video lasted approximately 1 min, and 200 sets (1000-5000 frames per set) were selected to build the training set. Third, the images were serialized, encoding images as 'xxxx.jpg' in the digital sequence. Finally, it was manually marked that the start-end frames of the drinking period and the coordinates of the region of interest (the snout and water fountain) for each set as the validation sets. The data sets presented in this study were mainly composed of PIG1, PIG2, PIG3, and PIG4, which were representative and covered Figure 2a a single-target sow in the day, and Figure 2b multi-target piglets in the dark.

a. Sow to drink in the day



b. Piglets to drink in the dark

Note: (a) ● or the sow's snout, ● for the water fountain; (b) ● ● ● ● ● ● mark different piglets and the water fountain.

Figure 2 Video pre-processing example

2.3 Methods for drinking behavior tracking

This study proposed a novel method for tracking the drinking behavior of pigs. First, the features of their drinking behavior were obtained on the basis of L-KOPT, and the spatial-temporal feature model of these animals' drinking behavior was established. Then, the improved KCF based on block sampling was used to identify the snout region. In addition, the eight-neighborhood idea was used to expand the sampling block. The relocation model of the snout was established. Finally, the DLC method was used to achieve target mapping between the pigs' snout and the water fountain. The trajectory tracking model was established to realize the drinking behavior judgment and track visualization. The research objective of the method in this study was to reduce the workload of manual labeling and to achieve high accuracy and timeliness. The technical route is shown in Figure 3.

2.3.1 Improved L-K pyramid optical flow method for feature detection

First, the instantaneous velocity is faster, and the optical flow value will have a large error when pigs raise their heads and lower their heads. In this study, the Gaussian pyramid was used to obtain a multi-layer image. Then, the optical flow was calculated in layers to improve the accuracy of the optical flow value.

Second, the initial optical flow features have a large volume of redundancy. In this study, principal component analysis (PCA) was used to eliminate the background optical flow and map the initial n-dimensional features to k-dimensional features.

Third, according to the current point coordinates ($[x_1, y_1]$) and displacement, the instantaneous velocity v of the optical flow point can be obtained. A threshold value of 10 pixels was set by the difference between the moving speed of pigs (v_1) and the water flow speed (v_2). When the speed exceeded 10 pixels, the event was inferred as water movement. Otherwise, it was the body movement of the pig. Meanwhile, the direction of the optical flow was defined in four areas: Right (−45°, 45°), Down (−135°, −45°), Left (135°, −135°), and Up (45°, 135°). The number of optical flow increases significantly in the Down direction due to the increase of water falling movement, which can explain the details of drinking water.

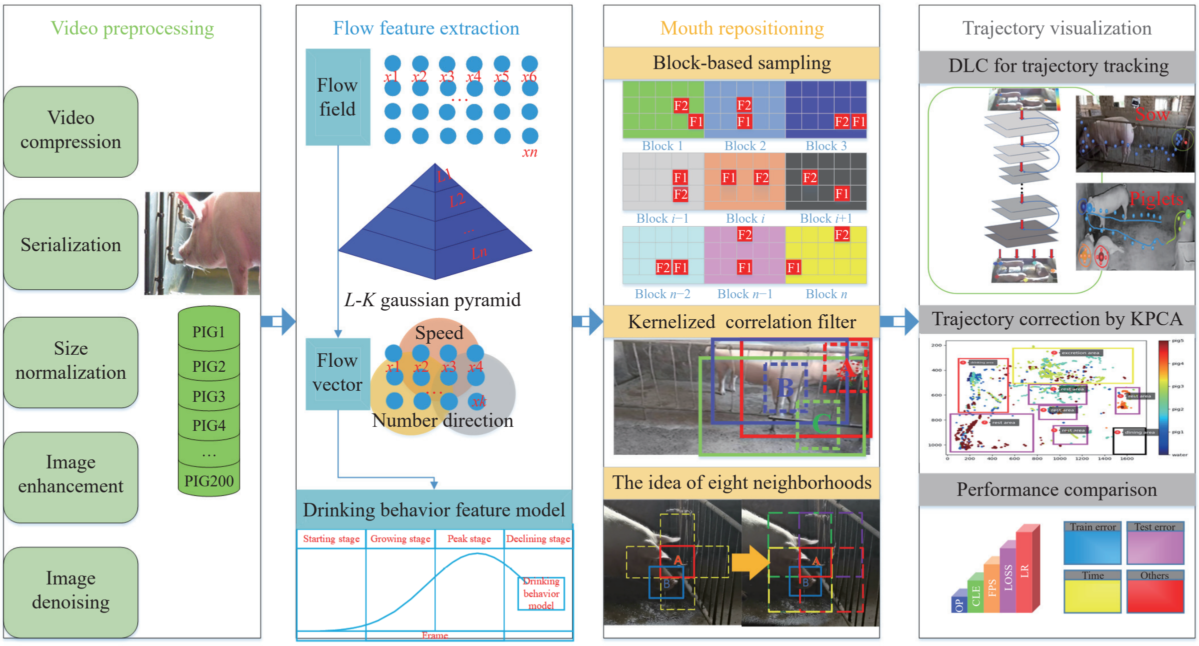
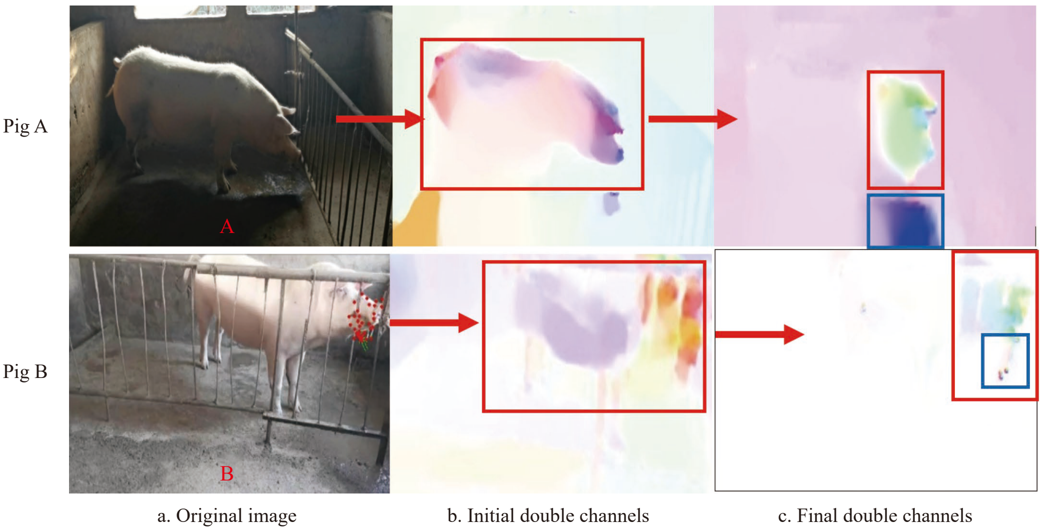


Figure 3 Overall process of this method

Finally, the double-channel feature extraction of pigs' drinking behavior is shown in Figure 4. After optimization in this study, the initial two-channel detection part could be accurately located from the whole pig to the head position. In addition, non-drinking behavior was detected in pig A, which extracted the head target and the ghost target. Meanwhile, drinking was detected in pig B, which focused on the head movement and water flow information. The water flow movement was a process of gradually strengthening and weakening. It could distinguish whether the same movement indicated that the animal was drinking.



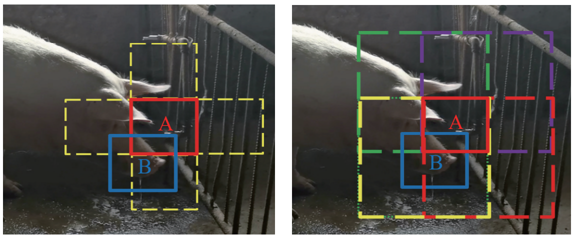
Note: The red box represents the target extracted by the L-K OPT method, which is optimized from the whole focus to the head. The blue box is the error target extracted.

Figure 4 Feature extraction based on L-K OPT method

Velocity vector and direction vector can be obtained in this research. However, the optical flow method could only extract features and could not solve the problems of ghosts, fence blocking, and the inability to locate the snout target.

2.3.2 Improved kernelized correlation filters for snout relocation

In this study, the KCF was selected as the snout target tracking method to solve the problem of optical flow tracing failure. On the one hand, the block sampling of the multi-channel merge feature of HOG and CN was adopted in this research to obtain the maximum response position of each sub-block. The final target position was obtained through the weighted average. On the other hand, the lost target relocation is shown in Figure 5. When the 67th frame was determined as a tracking error, the red frame area of the same position was found again in the 66th frame. It shifted to both horizontal and vertical directions to obtain four yellow sampling blocks, thus forming a "+" shape layout. However, a deviation was still present from the expected target area B. The eight-neighborhood idea was used to expand the sampling block by four times in the horizontal, vertical, and diagonal directions. Four larger sampling blocks were obtained as the green, purple, yellow, and red dotted line areas, and the yellow sampling position of the maximum response contained area B. It guaranteed the information integrity of the snout.



Note: A represents the initial target position, B represents the final target position, and the yellow, green, purple, and red boxes represent the sample boxes predicted by KCF, respectively.

Figure 5 Idea of multi-sampling eight neighborhoods

Therefore, the improved KCF algorithm based on block sampling and eight-neighborhood ideas in this research can make up for the disadvantages of the optical flow method in the target location of the pig's snout and realize the target relocation of the individual pig. However, this algorithm has limited ability in group target tracking.

2.3.3 Improved deepLabCut method for trajectory visualization

The application scenes of DLC[28] were mostly high-definition actions under ideal laboratory environment. It still required dozens of manual markers to train the model, which was a time-consuming process. The latest researches mainly add attention mechanism and other improvements to the deep learning algorithm, but there are still problems with the optimization of running speed and efficiency[29-31]. To realize the tracking of the drinking behavior trajectory of the sow and the piglets, we established a trajectory tracking model based on DLC, as shown in Figure 6. Aiming at the minimum frame marking and the maximum tracking efficiency, we improved the robustness and generalization of the piglets' drinking behavior trajectory model.

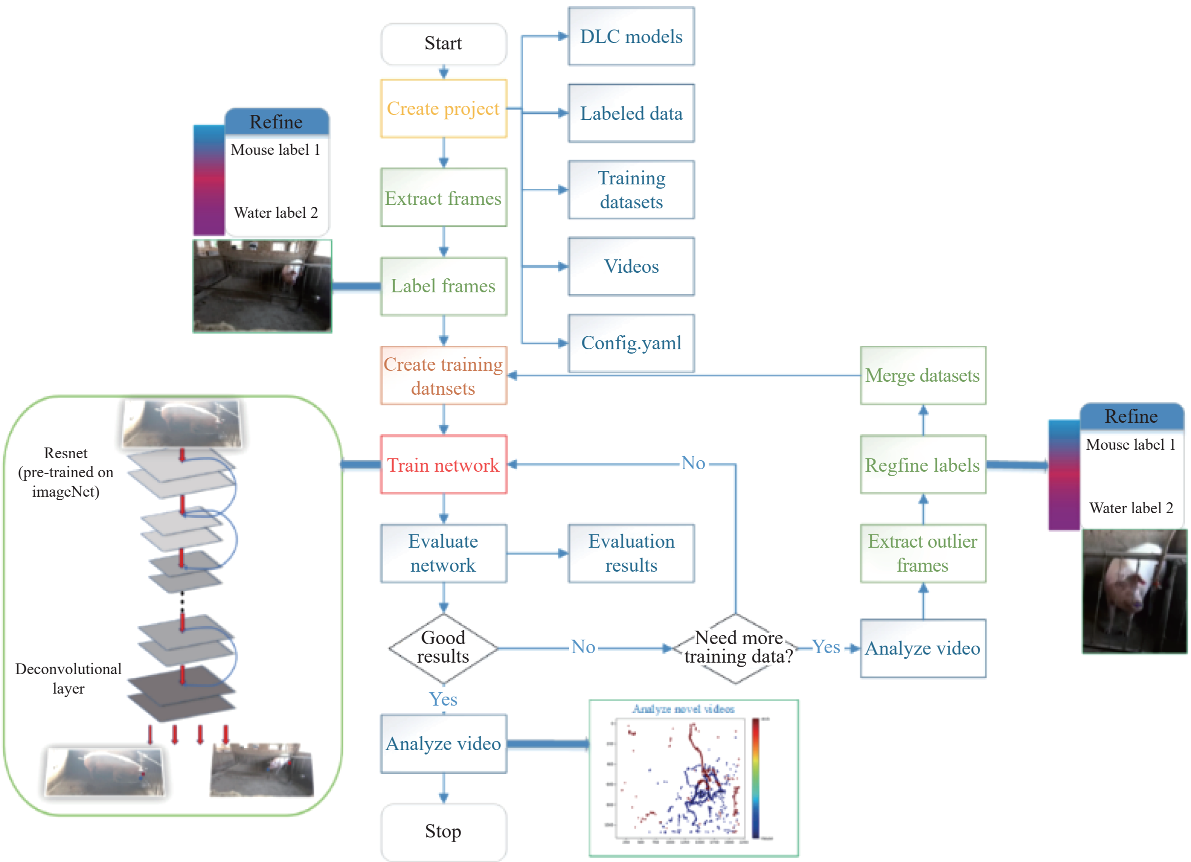


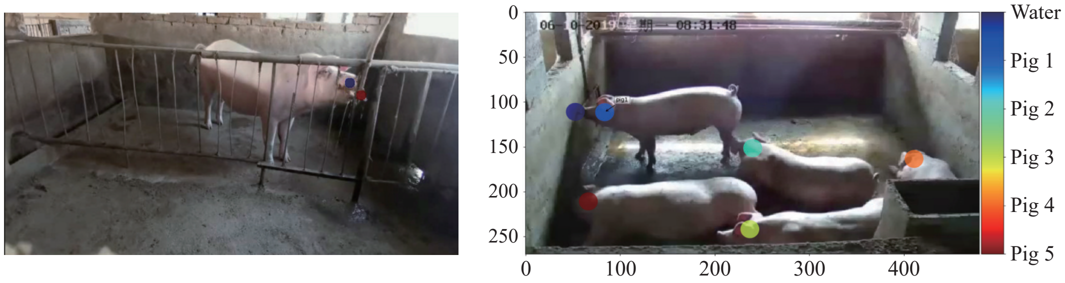
Figure 6 DeepLabCut work-flow

First, the labeling workload was reduced to less than 10, and the labeling quantity was amplified by matrix transformation.

Second, aiming at the redundancy of high-definition video information, we compressed the labeled samples and expanded the labeled area, as shown in Figure 7. It remained the scene semantics of the training samples and reduced the drift distance. Meanwhile, it assimilated abnormal trajectory, which enriched the positive correlation.

In addition, the ResNet50 neural network structure of this study is shown in Figure 8. The hard sample mining strategy was adopted to filter the easily classified samples, reduce the gap between similar samples, and increase the differences between various types of samples. The classification effect of the classifier would be improved.

Finally, the model generalization training was carried out, and different parameters, such as batch size, shuffle, training rate, and stride, were set to optimize the convolution layer. The stochastic gradient descent method was used as the model optimization strategy. In addition, the entire network used ReLU as the default activation function.



a. Image tagging of the sow

b. Image tagging of the piglets

Note: (a) ● for the sow's snout, ● for the water fountain; (b) ● ● ● ● ● ● mark different piglets and the water fountain.

Figure 7 Sampling point modification

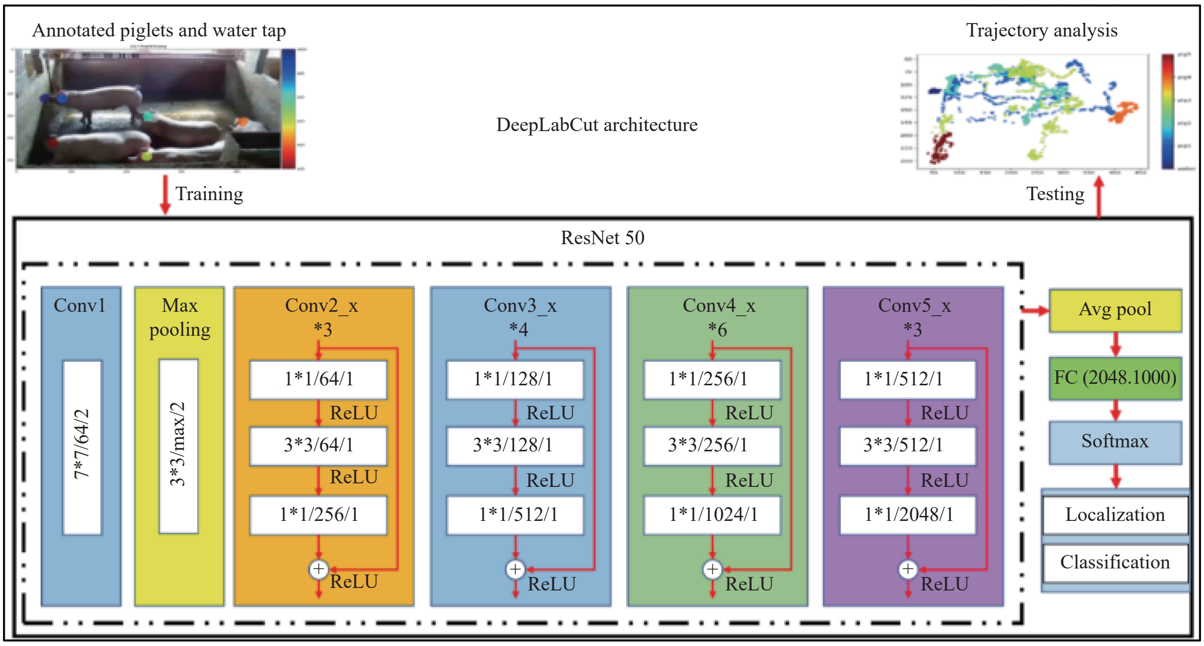


Figure 8 ResNet50 structure

3 Results and discussion

3.1 Drinking behavior feature model based on L-K pyramid optical flow

First, the optical flow amount of the original algorithm was reduced from an average of 3000 to approximately 40. The optical flow focused on the main parts of drinking water, such as the head and snout. Although the image resolution was reduced, the semantics of drinking water action remained unchanging, and the non-optical flow was eliminated.

Second, a quantitative model of optical flow features was established, as shown in Figure 9. For the initial model, the abnormal data exceeding the threshold (T<0 or T>200 or T>((t−1)+(T+1))) was corrected with the mean value. For the modified model, the results showed that the start time of drinking water was at frame 59 (the quantity increased), while the end time of drinking water was at frame 4641 (the quantity decreased), among which the first peak point was at frame 160.

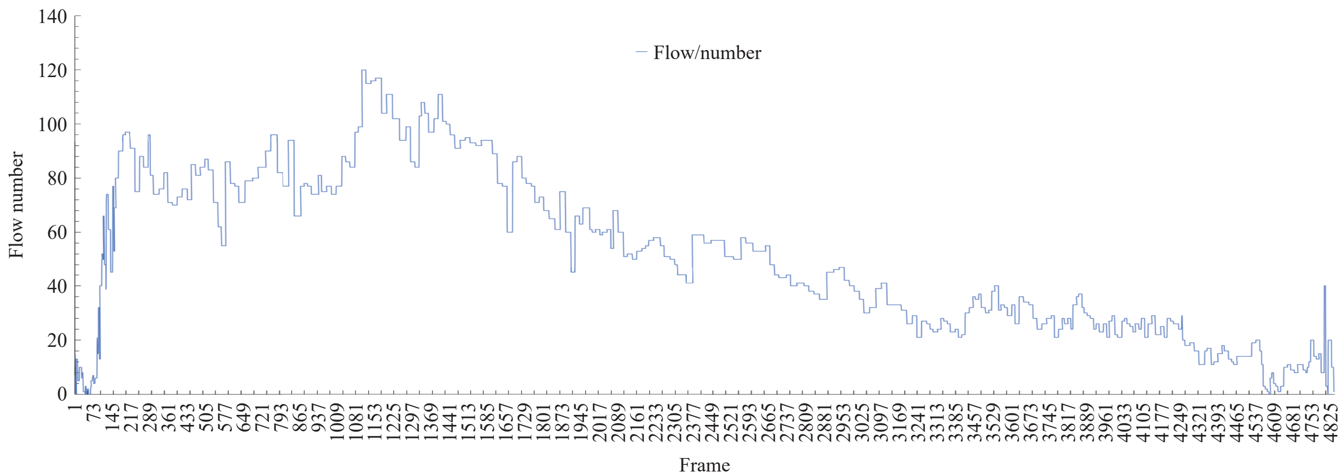


Figure 9 Eliminate abnormal optical flow points

Then, the velocity vector model of the drinking behavior was established, as shown in Figure 10. In frame 56, the number of v_1 and v_2 started to increase, thus indicating the start of the drinking period. At frame 110, the number of v_1 decreased and maintained at a low level, whereas the number of v_2 continued to increase to the first peak at frame 166. At frame 4621, the number of v_1 started to increase, thus indicating that the pig had left the water fountain and that the drinking period had ended.

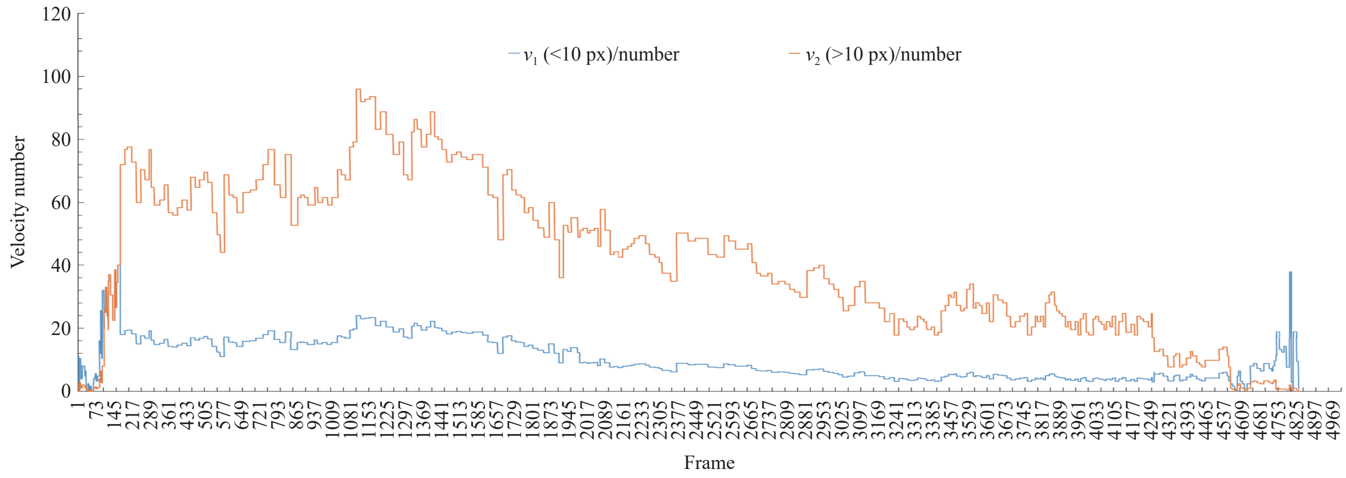


Figure 10 Drinking velocity model

Meanwhile, the direction vector model of the drinking behavior was established, as shown in Figure 11. The direction vector started to increase at frame 75, thus indicating that it was the start of the drinking period. At frame 100, the number of Down directions increased significantly. Then, the first peak was reached frame 149. The subsequent peak appeared continuously, thus indicating that the water flow was continuous. At frame 4589, the direction vector finally returned to normal, thus signaling the end of the drinking period.

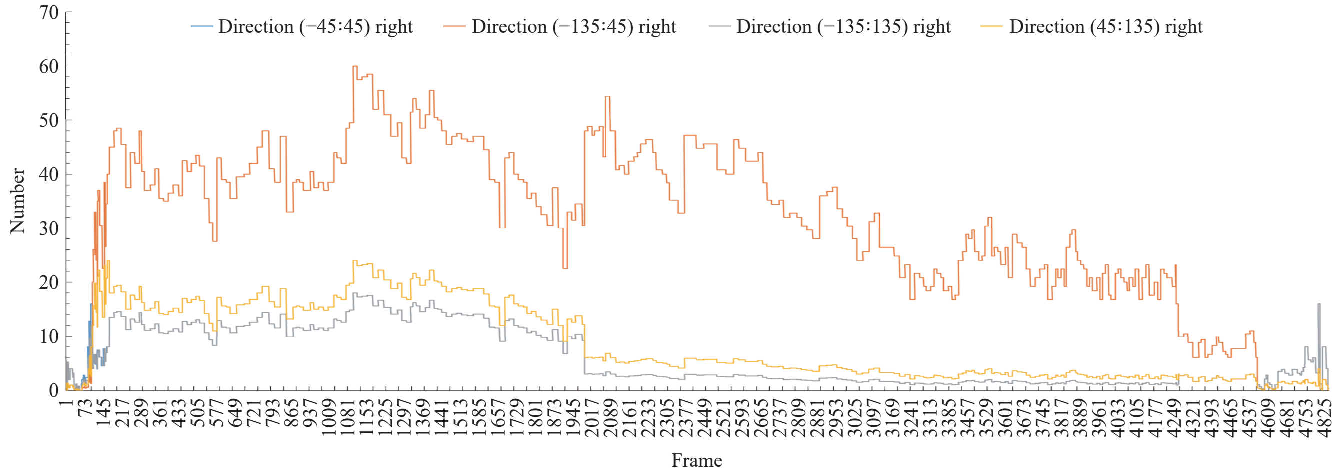


Figure 11 Drinking direction model

3.2 Snout relocation model based on improved KCF

When the threshold reached approximately 20, the relocation model achieved the optimal training accuracy of 98.89%. In addition, overfitting was expected to occur in the future. The qualitative evaluation results of different tracking algorithms are shown in Figure 12. In Figure 12a, the Kalman filter was seriously affected by noise, and targets were lost. In Figure 12b, Tracking Learning Detector (TLD) was located directly to the water fountain in the second half. Meanwhile, Discriminative Scale Space Tracking (DSST) extended the tracking range in Figure 12c; hence, it could only focus on the head position, and the snout position was not effective. In Figure 12d, Fast DSST (FDSST) could not be tracked continuously for a long time due to railing blocking and excessively fast motion speed. Then, in Figure 12e, KCF could continuously track the snout but lost the target in the scene of fast movement and scale change. Figure 12f demonstrated that the improved algorithm in this study basically realized the tracking of the snout region and was more stable than other trackers.

According to the qualitative evaluation, the improved KCF algorithm can continuously track the specific area of the fast-moving snout, which can solve the problem of target loss. The tracking effect is better than other trackers. The L-K OPT method is good at describing behavioral features. However, it cannot achieve target positioning and tracking. The improved KCF solves the problem of snout relocation. When the snout location coordinates fit with the water fountain, the judgment result of drinking behavior based on L-K OPT can be further verified.

3.3 Trajectory tracking model based on deepLabCut

The tracking results of the drinking trajectory of the group piglets are shown in Figure 13.

Figure 13a demonstrates the manually annotated trajectory of the datasets of PIG3 and PIG4. In PIG3, blue was the water fountain, light blue was pig 1, cyan was pig 2, yellow was pig 3, orange was pig 4, and red was pig 5. In PIG4, blue was the water fountain, light blue was pig 1, cyan was pig 2, orange was pig 3, and red was pig 4.

Figure 13b shows the X-axis and Y-axis displacement of the snouts in each frame, which were approximately 10-20 pixels/frame. The maximum detection times were 2000 and 400 times respectively, and no long-distance trajectory drift occurred.

a. Tracking results of Kalman Filter b. Tracking results of TLD c. Tracking results of DSST

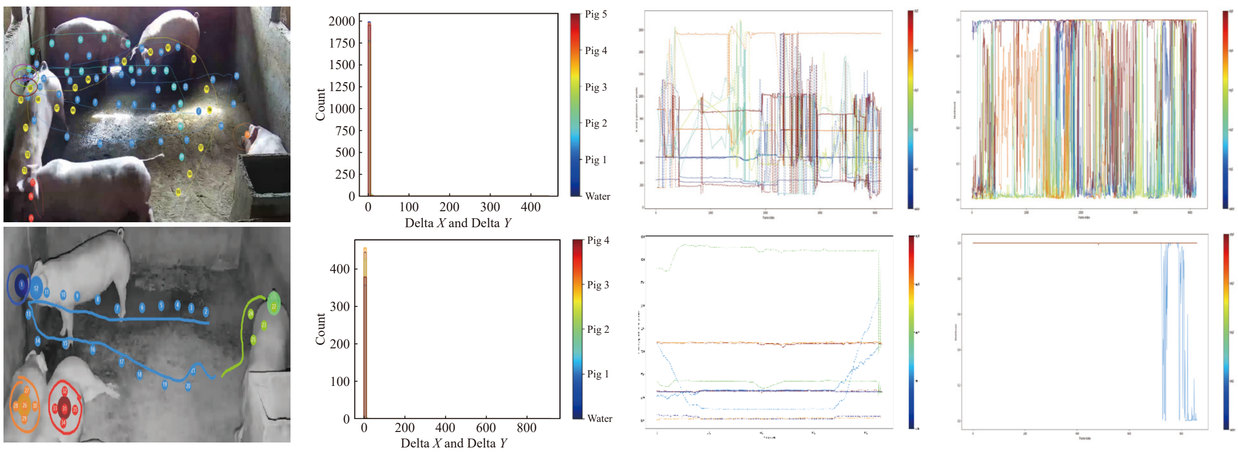
d. Tracking results of FDSST e. Tracking results of KCF f. Tracking results of our method

Note: TLD: Tracking Learning Detector; DSST: Discriminative Scale SpaceTracking; FDSST: Fast DSST; KCF: Kernelized Correlation Filter; Our method is the proposed method in this study.

Figure 12 Tracking results of different algorithms

PIG3

PIG4



a. Manually trajectory b. Delta X and Delta Y c. x and y position d. Likelihood

Figure 13 Drinking behavior tracking of PIG3 and PIG4

In frames 500-1800 of PIG3 in Figure 13c, the blue and light blue were positively correlated, thus indicating that pig 1 was drinking water. In frames 1800-2200, blue and cyan remained consistent, thus indicating that pig 2 was drinking water. In frames 3000-3200, the blue was the same as light blue, thus indicating that pig 1 was drinking again.

In frames 180-680 of PIG4, the blue and light blue were positively correlated, thus indicating that pig 1 was drinking water and the judgment effect was very good.

Figure 13d shows the likelihood of group trajectory. The likelihood of PIG4 at night was higher than that of the PIG3 in the day. However, the complex scene of PIG3 had numerous trace losses during the day. In addition to the water fountain, pig 4, and pig 5, the group identification and track loss problems of pig 1, pig 2, and pig 3 still needed to be further solved.

3.4 Discussion

3.4.1 Feature model performance

In terms of the construction of the drinking behavior feature model, the improved L-K OPT method could accurately extract the feature vectors of drinking water and construct the feature vector model of the space-time dimension. The results showed that the amount of optical flow increased and then decreased progressively. First, the head movement was mainly an oblique movement in the form of gathering points, and the vertical movement was secondary. The water flow was mainly vertical downward in linear form and supplemented by oblique movement. Second, the average normal movement speed of the pigs was 8 pixels/frame, while the average water flow speed of the pigs was 15 pixels/frame. The velocity between the two had a significant difference. Third, the direction vector Down(−135°,−45°) and velocity vector V2 (>10 pixels) significantly increased when the pig was drinking water, which could be used as the key features to determine whether the animal was drinking water. Lastly, the determination results, such as the drinking time and the starting time of pigs could be accurate to the frame level. The error was within 30 frames, which was ignored.

3.4.2 Snout relocation model performance

In terms of the reconstruction of the snout relocation model, the improved KCF method based on block sampling and the eight-neighborhood idea was able to focus on the continuous tracking of the snout efficiently. Moreover, the problem of target loss was basically solved after expanding the area of the sampling block four times.

The proposed method was quantitatively compared with the existing trackers. The public datasets OTB50 and the datasets PIG1 and PIG2 were selected to study the algorithm generalization. As shown in Table 1, our method's OP reached 95% on average, CLE was reduced to 3 pixels, and the speed reached more than 300 fps, which was 30% higher than the traditional KCF. Meanwhile, our method was 30 times faster than the Kalman filter, 5 times faster than TLD, 4 times faster than DSST, and approximately 1.5 times faster than FDSST. The evaluation index demonstrated that our method greatly improved the generalization ability.

Table 1 Comparison results of tracking methods

Datasets	Indexes	Kalman	TLD	DSST	FDSST	KCF	Ours
PIG1	Precision/%	38	63	63.2	83.6	82.5	94.9
	Error/pixels	63.76	42.5	44.53	12.3	8.64	3.4
	Speed/fps	27.4	86.6	74.92	164.4	217.9	312.26
	Time/s	428.65	76.05	62.64	31.15	20.18	15.60
PIG2	Precision/%	45	57	54.7	74.8	72.4	92.7
	Error/pixels	70.55	35.1	54.75	25.6	14.4	4.1
	Speed/fps	32.5	93.3	63.57	193.1	166.1	309.02
	Time/s	480.78	58.87	50.69	33.94	25.26	16.81
Basketball	Precision/%	34.5	68	71	76	92.4	96.3
	Error/pixels	52.21	36.2	47.1	21.5	4.71	2.1
	Speed/fps	25.1	64.7	43.6	83.3	215.05	310.59
	Time/s	91.52	15.12	12.36	7.43	6.21	3.47

Note: PIG1 had 4870 frames, with a pixel size of 960×540; PIG2 had 5196 frames, with a pixel size of 960×540. Basketball had 725 frames, with a pixel size of 576×432. TLD: Tracking Learning Detector; DSST: Discriminative Scale SpaceTracking; FDSST: Fast DSST; KCF: Kernelized Correlation Filter; Ours is the proposed method in this study.

3.4.3 Trajectory tracking model performance

In terms of the construction of the trajectory tracking model, the trajectory tracking of the drinking behavior of the piglets was realized on the basis of DLC. The lowest test error result was 3.88, and the lowest train error was 1.27. The batch size (1, 4, 8, 16, 32, 64) was used to test the processing speed (FPS) of different magnitudes. The speed of GTX960M could achieve a value of 440 fps, whereas 8-core CPU could only achieve a maximum of 70 fps. The optimization of the learning rate (0.02/0.005/0.002/0.001) was carried out. In the first 5000 iterations, the loss value was reduced to 0.002, and it could reach 0.0002 after 1 million iterations. The optimal learning rate was 0.005, and the algorithm was more robust.

3.4.4 Trajectory correction analysis

The most complex drinking behavior trajectory of the group piglets is shown in Figure 14. The trajectory drift and loss mainly occurred in the 1-drinking area, 2-excretion area, and 3-rest area with dense shelter, while 4-7 were rest areas with little interaction. The 8-dining area was not included in this study. The trajectories that needed to be corrected mainly included internal overlapping trajectories and external drift trajectories.

The corrected trajectory results of the data sets are shown in Figure 15. In Figures 15a and 15b, the abnormal trajectories detected were not only limited to the edge of the data set but also located in the interior of the data set. The abnormal trajectories in the velocity and space dimensions had been greatly modified. Compared with the original results, Figures 15c and 15d had a more evident effect, and their synchronization and correlation were improved.

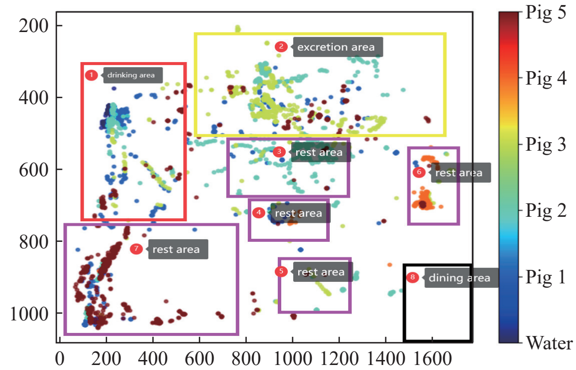


Figure 14 Main areas of drinking behavior tracking

The results demonstrated that the drinking behavior of group piglets was more difficult to track than that of the individual sow, which mainly solved the problem of dynamic scale change. It realized multi-target tracking and the correction of at least three trajectory routes. The drinking behavior of pigs at night was stable, with the average drinking time being 20 s. However, the group piglets in the day had a high frequency and large amount of exercise, in which the average drinking time was 15 s. The trajectory was intricate, and the route was diverse, which was easy to lose and drift. Based on the improved DLC method, it could solve the problems of the dynamic change of the individual sow, the day-night change of the group piglets, and the tracking of the drinking trajectory in a complex environment. Regardless of the fixed perspective, dynamic perspective, or scale change, our method showed an evident positive correlation, and the performance of the algorithm was superior.

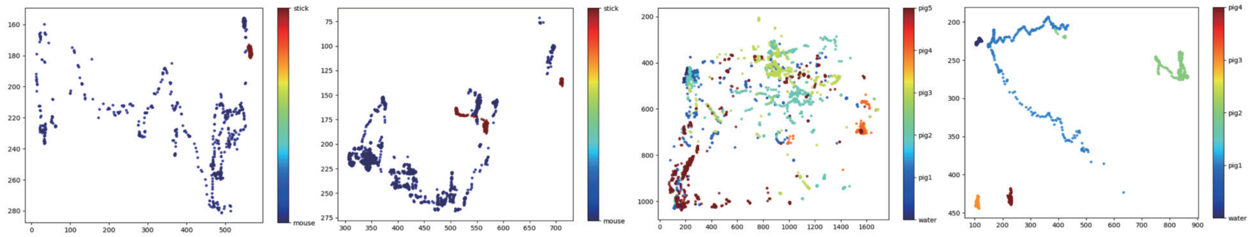
4 Conclusions

The proposed method in this study could detect the drinking behaviors of the individual sow and the group piglets during the day and at night. Furthermore, it could effectively deal with the problems of fast movement, target relocation, and multi-target drinking tracking loss. The novel method of judging drinking behavior was creatively explored from the angles of water flow movement and trajectory clustering.

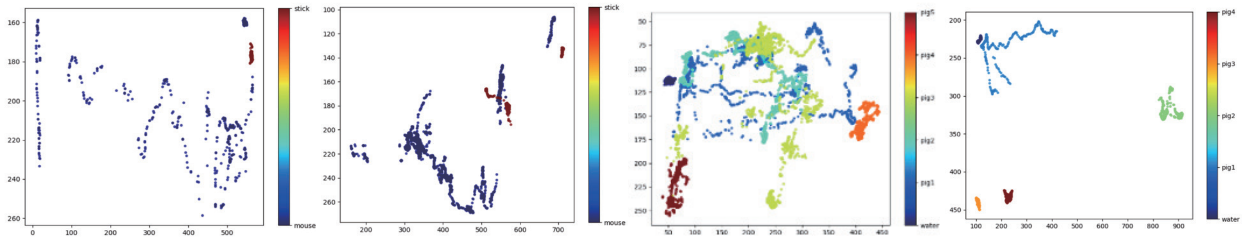
1) To solve the problem of the spatial and temporal information scarcity of drinking behavior features, multi-dimensional vectors, such as speed, direction, and time, were added to the feature model. According to the water flow movement, it could judge whether the pig was drinking water, detect their drinking time, and collect action details;

2) Focusing on the problem of sampling loss caused by the fast movement of the snout, the idea of eight neighborhoods was used to expand the sampling block. The repositioning of the snout was realized, and the correlation mapping between the snout and the water fountain was formed;

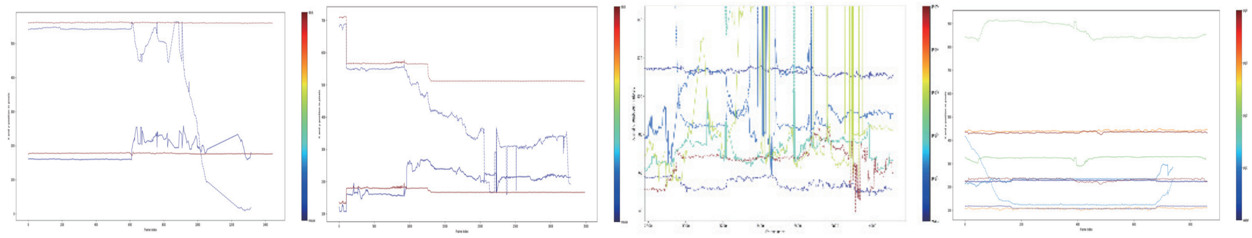
3) Aiming at the problem of the real-time tracking and abnormal track correction of the drinking behavior of pigs, it combined with the acquired spatial and temporal features to correct abnormal trajectory, judge the drinking behavior accurately, and realize the visual tracking of trajectory.



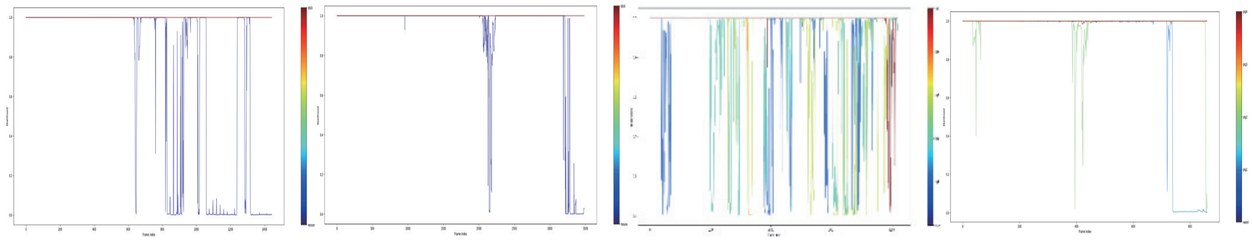
a. The initial trajectory map



b. Corrected trajectory map



c. Corrected X and X position in pixels



d. Corrected likelihood

Figure 15 Drinking behavior tracking correction

The method in this study avoided the loss of the traditional Internet of Things method, which reduced the reliance on manual annotation. The breakthrough and innovation in the generalization and robustness of the method in this study were verified from the perspectives of quantitative analysis and qualitative evaluation.

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