Monitoring behavior of poultry based on RFID radio frequency network

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Abstract: Poultry behavior monitoring is an important basis for the poultry disease warning. Manual monitoring is mostly used nowadays. In this work, the automatic monitoring system for assisting manual monitoring was examined. Sophisticated data mining techniques were used to leverage the data collected by RFID devices. Specifically, (1) weighing sensors and wireless networks of Multiple RFID-tag-collector groups were used to monitor the poultry behavior; (2) RFID tags were putted on individual poultry so that the moving time of the poultry between two RFID-tag-collectors could be recorded. Thus, the characteristic functions of poultry behaviors such as speed, ability to snatch food and resting time could be extracted based on the distance between two RFID-tag-collectors and the relevant time parameters; (3) the sick, normal, active and other poultry groups were categorized by using the K-means method which utilizing the behavior characteristics and poultry weight data in data mining. The results demonstrated that accurate classifications could be obtained according to the poultry characteristics, and the clustering results matched with the results obtained by manual method to identify the poultry groups. Consequently, the technique in this paper has great potential for large-scale poultry disease warning and poultry classification.

Keywords: poultry behavior, monitoring, cloud computing, internet of things (IoT), radio-frequency identification, data mining
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1 Introduction

The animal behaviors such as feeding, resting and running are important indicators for judging the animal's health and diseases. In recent years, complex wireless sensor networks (WSN) and image processing are the predominant technologies used for monitoring poultry behaviors. When Radio Frequency Identification (RFID) is adopted in agricultural informatization, it is often used to identify different individuals. And yet, there are no reports about monitoring the animals' behavior directly by RFID. In this research, RFID technology and data mining method are utilized to observe the behaviors of free-running animals. It not only lowers the cost of the system greatly but also improves the feasibility in system deployment.

In recent years, progress has been made on the study of animal behaviors[1-7]. Leroy et al.[8] adopted image processing technology to observe the hens' growth, and analyze their abnormal behaviors in different states.

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Although this method saves both time and labor, with the inherent limitations of image processing algorithms, it does not perform well in terms of accuracy and resolution. In particular, this technique has difficulties in identifying animals' ID tags as well as fast-moving small animals[9,10].

In contrast, other researchers used WSN technology as the means for tracking animal behaviors[11]. Commonwealth Scientific and Industrial Research Organization (CSIRO) in Australia utilized WSN to build up an intelligent farm. They put collars which contain global position system (GPS) and wireless sensor nodes on the cattle in order to record their behaviors as well as the corresponding environment. Kwong et al.[12-14] adopted WSN to monitor the cattle for timely discoveries of the lameness or other sickness. Nadimi et al.[15] suggested to use WSN to measure the rotational angle and the moving speed of cattle necks, and categorize cattle behaviors with classification tree algorithms. Yin et al.[16] created a digital intelligent system using WSN to monitor the cows' behaviors, which can predict their heat periods, sickness and so forth. On one hand, WSN can monitor the animal behaviors more precisely; on the other hand, there are several problems of WSN[13]: Firstly, the wireless sensor nodes easily suffer the intentional or unintentional damages from the animals. Secondly, the nodes are vulnerable to environmental pollution. Thirdly, the cost of such nodes is high. Last but not least, due to the size of nodes, it is difficult to attach them in small animals.

Due to the defects of the data acquisition terminal in WSN, and the high pollution, strong destructiveness, and low benefit in animal raising, the system discussed in this paper will reduce the defects of it. Instead, the advantage of the big data analysis on the cloud computing platform running at the back end will be employed. By using RFID collectors to collect chicken's ID and time parameter, the behavior characteristics can be dug out[17]. Then the active, the normal, the sick poultry groups can be classified through clustering method.

2 Material and methods

2.1 Overall framework of the system design

The chicken farm in Jianggao Town of Guangzhou was chosen as the research site and the free-range chickens as the research object. By monitoring the behavior characteristics of chickens, this project established the disease warning system and automatic classification assistant system. In this farm, the chickens are classified feeding according to their quality. In order to make the results more reliable, the first class fence with 13 chickens was taken as the experiment point. And 5 sick chickens from the third class fence and 6 normal chickens from the second class fence were added into the experiment point.

According to the standard of farm classification, chickens in the first class fence have strong activity and proper weight (about 1.5 kg). And chickens in the second class fence have less activity and higher or lower weight. And chickens in the third class fence have the worst activity. In this system, the RFID collectors were used to collect data. By calculating characteristics such as the order of arriving to feeding site, the resting time and speed, chicken's activity can be identified.

The activities of chickens such as eating in the feeding site and moving around between several fixed resting sites, were recorded in this system by placing RFID-tag-collectors in these sites[18]. In the research, each chicken wore the foot ring with RFID-tag (the tag code of the foot ring represents the ID of chicken), and RFID-tag-collectors were placed in those fixed resting sites and entrances of the feeding site for continuously gathering the ID of chickens with the frequency of 3 times per second (the collectors also recorded acquisition time). Then the data from collectors were uploaded immediately by wireless transmission nodes.

The weighing sensor, RFID-tag-collectors and wireless transmission nodes were placed at the entrances of the feeding site (as shown in Figure 1), in order to obtain a chicken's weight, ID and the time of arrival at the feeding site[19,20], so that the behavior characteristics of chickens such as 'weight' and 'ability to snatch food' can be analyzed. Besides, RFID-tag-collectors were also placed in the resting sites to get the moving time of chickens between two sites, according to the collected ID and the arrival time to this site. Then the behavior characteristics such as 'speed' and 'resting time' can be calculated.

The K-means clustering method is used to cluster behavior characteristics of chickens so that the chickens can be classified into the active, normal and sick. Through the above steps, the chicken diseases can be detected in time and the accurate growth states of the chickens in the fenced area can be known immediately.

At last, the experiment was repeated to verify the results of clustering classification. Besides, the results of system clustering were also compared with the farm classification.

The flow diagram of the system is shown in Figure 1.

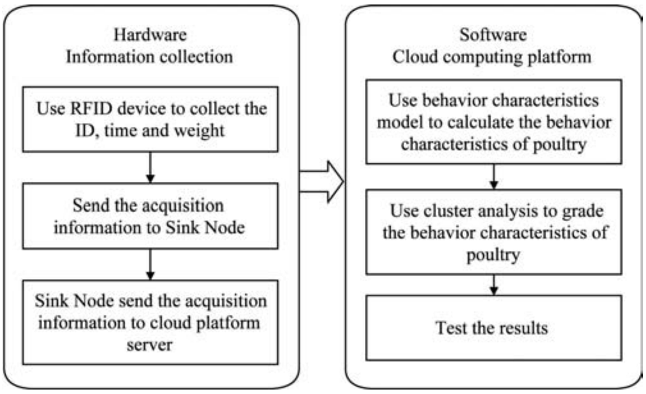

Figure 1 Flow diagram of the system

2.2 Hardware design of the system

In the project, two RFID-tag-collectors were placed in two different resting sites, one with a weighing sensor was placed in the feeding site[21-24]. And these devices transmitted data to the sink node through two wireless transmission nodes. Then the sink node would transmit these data to the cloud computing platform and database, as shown in Figure 2. RFID-tag-collectors are JT900A and the scanning cycle is 300 ms. Weighing sensor is YZC-1B and its comprehensive error ≤±0.030%. All chickens wore RFID-tags with F43 high frequency IC. In the resting sites, the sampling frequency of RFID-tag-collectors is 3 times per second. Using these two collectors, the hardware system can record each ID of chickens and the time when it appears. And by using the behavior model software in this system, the resting time, the speed and the frequency of moving between different resting sites of a chicken can be calculated (the distance between two different resting sites is known). In the feeding site, the sampling frequency of weighing sensor and RFID-tag-collector is also 3 times per second. These two devices can provide the weight of chickens and record the order of arrival of chickens when they snatch food[25,27].

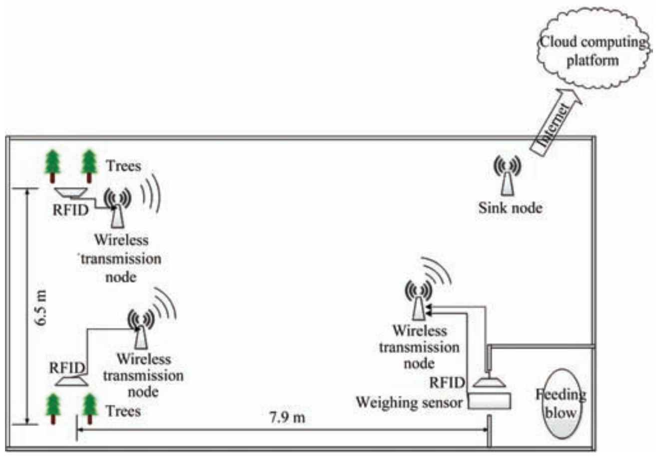

Figure 2 Hardware layout of the system

2.3 Software design of the system

The poultry behavior includes speed, ability to snatch, resting time etc. In this study, these RFID-tag-collectors and weighing sensor were placed in the resting sites and the feeding site to collect the chicken's ID, arrival time and weight so that the behavior characteristic model and the weight model of chickens can be built. In order to online discover the diseases, the behavior characteristics were classified through clustering method. Then the sick chicken groups would be found out.

In every collection, the data of chickens with good quality are not always better than that of other chickens. However, the chickens with good quality will behave better in the ability to snatch food, resting time, speed etc. These are high probability events. The conventional method to deal with the data of high probability events is to average all the values after removing the maximum and minimum values. Through this method, the data of low probability events will be diluted.

2.3.1 Construction of behavior characteristic models and weight models of chickens

1) Characteristic model of chickens' moving speed

As we know, strong chickens run fast. To collect the data of behavior characteristics, RFID-tag-collectors were placed in the resting sites, in which the speed $V(i)$ can be calculated from the distance (S) between two collectors and the running time $T(i)$ recorded by two collectors[30,31]. In this experiment, the distance between two RFID collectors is 6.5 m. And the distances between two collectors and the feeding site are 7.9 m and 10.23 m respectively.

The formula is:

$$V(i)=\frac{S}{T(i)} \tag{1}$$

2) Characteristic model of chickens resting in the resting sites

It is well known that sick chickens are not active. Instead of moving around, they stay in the resting sites for a long time. In this situation, the collectors in the resting sites will continuously acquire the ID of the chicken in a period of time.

The formula for chickens' resting time in the resting sites is:

$$Stayings(i)=Staying_{last}(i)-Staying_{first}(i) \tag{2}$$

where, $Staying_{last}(i)$ is the resting time of chicken i; $Staying_{last}(i)$ is the time of the last record for chicken i continuously staying in the resting sites; $Staying_{last}(i)$ is the time of first record for the chicken i beginning staying.

3) Characteristic model of snatching food

In this experiment, one RFID-tag-collector was placed in the entrance of the feeding site. It is known to all that active chickens have proper weight and excellent ability to snatch food. According to this point, at feeding time, the active chicken will run to the entrance of feeding site quickly. Thus, by recording the order of chickens' arrival at the feeding site, the chickens' ability of snatching food and flexibility can be known[28,29].

4) Characteristic model of chickens' weight

The data of chicken's weight and ID were collected by the weighting sensor and RFID-tag-collector at the feeding site. To avoid the situation that two chickens stand on the weight sensor at the same time, the entrance of weight sensor was designed as narrow as possible so that only one chicken could stand on it at a time. Besides, the system averages the data values of 3 d after removing the maximum and minimum. Then the reference weight values of chicken in this period could be acquired.

In order to make the test data of weight closer to the real value, the system removes the maximum and the minimum value from the collected data, and then takes the average value as the weight of a chicken:

$$G(i)=\frac{\sum_{j=1}^{n}g(i,j)-g_{\min}(i)-g_{\max}(i)}{n-2},\quad (1\le j\le n) \tag{3}$$

2.3.2 K-means clustering method for the recognition of chickens' diseases and quality

The behavior characteristics of the chickens with uniform qualities are more similar. This makes it possible to group them into one cluster. According to K-means clustering method, the chickens in the study are divided into three clusters: the active, the normal and the sick. The health condition of all the chickens in the farm will be monitored precisely by this system. Once the sick are discovered, something can be done timely. Besides, the current detailed growth state of the chickens can be acquired as well.

K-means accepts a parameter k and classifies m data objects into k groups so that the groups can meet the following conditions. In K-means, the similarity of the objects belong to the same cluster is high while that in different clusters is low[32,35]. Similarity can be measured by distance, which means that the higher the similarity between two objects in the same cluster, the shorter their distance. Using Euclidean distance formula, the distance between two objects can be calculated as follows:

$$D(i,j)=\sqrt{\sum_{p=1}^{n}(x_{ip}-x_{jp})^2}\,,$$
$$i=(x_{i1},x_{i2},......,x_{ip}),\ j=(x_{j1},x_{j2},......,x_{jp}) \tag{4}$$

where, $i=(x_{i1},x_{i2},......,x_{ip}),\ j=(x_{j1},x_{j2},......,x_{jp})$ are two p-dimension objects; $D(i,j)$ is Euclidean distance between i and j.

In this study, the behavior characteristic vector of chicken i is (x_{i1}, x_{i2}, x_{i3}, x_{i4}). The variables x_{i1}, x_{i2}, x_{i3}, x_{i4}, represent the chicken's ability to snatch food, weight, speed and resting time in the habitat respectively. Similarly, the behavior characteristic vector of chicken j is (j_{i1}, j_{i2}, j_{i3}, j_{i4}). If these two chickens are active, they will have closer characteristic value and smaller distance $D(i,j)$ according to Equation (4). Therefore, chicken i and chicken j can be grouped into the same cluster.

The flow of classifying m data points by K-means is as follow:

(1) Select k points as the first cluster centers. $c_i = \sum I_i \in |L_j|$;

(2) Calculate the distances d between point I_i and every cluster center c_j respectively. Then put it into the cluster with the shortest distance. $d = |I_i - C_j| \, (i \in \{1,2,...,m\},\ j \in \{1,2,...,k\}$;

(3) Take the average value of all points in the clusters as the new cluster centers.

$$c_i = \sum I_i / |L_j| \ I_i \in L_j$$

$|L_j|$ is the number of the points in L_j.

(4) Repeat step (2) and (3) until no change in every cluster.

3 Results and Discussion

3.1 Result of clustering

The chicken in this farm are classified into 3 groups for feed. Chickens in the first class fence are the most active, chickens in the second class fence are normal, and chickens in the third class fence are sick. To verify the result of clustering, considering the situation of the farm, six normal chickens from the second class fence (03190001, 03190002, 04160001, 070B001B, 090A0037, 090A004B) and five sick chickens from the third class fence (070B0019, 090A0050, 070A0061, 090A0047, 090A0063) were added into the first class fence which have 13 active chickens. The behavior characteristic data and weight data of chickens are shown in Table 1.

As shown in Figure 2, radio frequency network was set in the fence. The data of 3 d (about 400 thousand records) were selected as the experiment data for case analysis. In Table 1, the values of four behavior characteristics were the average of all data in the period, acquired by calculation with the characteristic model. The characteristic data are shown in Table 1, in which, the higher the value in the first column (ability to snatch food), the more active and stronger in snatching food the chicken is. And the values in the column 'Standard weight' were the weights artificially measured by a scale. After standardization, parts of the behavior characteristic data are shown in Table 2.

Table 1 Behavior characteristic data and weight data of chickens

RFID	Ability to snatch food/level	Weight /kg	Moving speed /m·s^{-1}	The resting time/s	Standard weight /kg	Farm classification /level
03190001	0	2	0	7.4	2.46	2
03190002	0	2	0	1.5	3.010	2
03190004	0	1	0	5.8	1.620	1
04160001	0	2	0	1.8	2.000	2
070B0019	0	2	0	10	2.900	3
070B001B	0	2	1	2.6	2.470	2
090A0033	0	1	0	4.9	1.520	1
090A0037	0	2	0	2.0	2.150	2
090A0040	0	1	0	9.6	1.460	1
090A0042	0	1	0	4.6	1.480	1
090A0043	0	1	0	2.1	1.830	1
090A0048	0	2	0	2.0	1.830	1
090A004A	0	1	0	11	1.540	1
090A004B	0	1	0	4.5	1.840	2
090A0050	0	2	0	6.4	2.500	3
090A0051	0	2	0	7.1	1.800	1
090A0055	0	1	0	5.5	1.740	1
090A0057	0	1	0	2.2	1.590	1
090A0058	0	1	0	9.9	2.010	1
090A0059	0	1	0	5.5	1.600	1
090A005D	0	1	0	2.6	1.450	1
070A0061	0	2	0	20	2.320	3
090A0047	0	2	0	18	2.300	3
090A0063	0	2	0	16	2.400	3

Table 2 Parts of the behavior characteristic data after standardization

RFID1	Ability to snatch food	Weight	Moving speed	The resting time
031900011	0.24125	−1.24263	0.60106	−0.05954
03190002	−1.77107	−1.46457	1.64902	1.0626
03190004	0.973	1.28193	−0.39223	0.25092
04160001	−0.24354	−0.21616	0.56916	0.99901
070B0019	−0.12463	−1.46457	−0.58815	−0.63556
070B001B	−0.55453	−1.13166	3.35765	0.84939
090A0033	0.78092	1.17096	−0.46513	0.41176
……	……	……	……	……

According to the flow of K-means in 2.3.2, cluster centers of the active, the normal and the sick can be acquired, as shown in Table 3.

Table 3 Cluster centers (three clusters)

	cluster1	cluster2	cluster3
Ability to snatch food	0.50520	−0.49965	−0.91492
Weight	0.75086	−0.95966	−1.14276
Moving speed	−0.17970	1.43305	−0.92987
The resting time	0.20497	0.76112	−1.33503

In Table 3, the higher the value of the column 'Ability to snatch food' is, the stronger the ability to snatch food is.

And the higher value of the column 'weight' means that the weight is close to 1.5 kg. The higher the value of the column 'Moving speed' is, the faster the chicken is. The higher the value of the column 'resting time' is, the less the resting time is. It can be seen from Table 3 that chickens in Cluster 1 have the strongest ability to snatch food and proper weight closing 1.5 kg. That means these chickens are the most active and strongest ones, belonging to the first class cluster.

The chickens in Cluster 2 have the fastest speed and the least resting time. Their abilities to snatch food rank second. And their weights are little higher than the standard weight value (1.5 kg). In all, although these chickens run fast, the distance between the feeding site and resting site is just a few meters, making the advantage of their fastest speed weaken. When snatching food, these chickens didn't behave as well as the active chickens in Cluster 1. Besides, the weights of these chickens are not in accordance with the standard. Their body sizes are little bigger or smaller. And they have a lack of good flexibility. Thus, these chickens belong to the second class cluster.

When it comes to Cluster 3, the 4 characteristic values of the chickens in this cluster are all bad. Thus they are the sick ones, belonging to the third class cluster.

At last, according to Equation (4), the distance between chicken and cluster center can be calculated by using the characteristic values in Table 2. The shortest distance between chicken and cluster center decides which cluster the chicken belongs to. .

The results of K-means clustering are shown in Tables 3-5.

It can be seen from Table 4 that these 24 chickens are classified into 3 clusters. The chickens in the first class cluster are the most active. And the chickens in the third class cluster are the sick ones, having the worst qualities. In the second cluster, most of chickens have big body size and a lack of flexibility. Comparing the result of system clustering with that of farm classification, only one chicken (090A004B) is not consistent while the other 23 chickens are completely consistent. The consistency ratio is 96%. This means that the method in this study can assist manual monitoring in large scale chicken farm usefully. And the system can detect sick chickens in time and assist the chicken classification.

Table 4 Cluster members (three clusters)

RFID	cluster	Distance	Farm classification
03190001	2	1.41233	2
03190002	2	1.41739	2
03190004	1	0.74037	1
04160001	2	1.19217	2
070B0019	3	1.15506	3
070B001B	2	1.93506	2
090A0033	1	0.61378	1
090A0037	2	0.62471	2
090A0040	1	1.03392	1
090A0042	1	1.99122	1
090A0043	1	0.79348	1
090A0048	1	1.68308	1
090A004A	1	1.46280	1
090A004B	2	0.89417	2
090A0050	3	1.73822	3
090A0051	1	0.97080	1
090A0055	1	0.82600	1
090A0057	1	0.82074	1
090A0058	1	0.92855	1
090A0059	1	1.45352	1
090A005D	1	1.34628	1
070A0061	3	1.42257	3
090A0047	3	0.91365	3
090A0063	3	0.55324	3

3.2 Result validation of clustering

It is very different between the sick chickens and the normal or active chickens in the aspects of resting time, ability to snatch food and speed. Normally, the sick chickens will stay under the trees or the feeding site. And the RFID collectors will continuously get their ID. At feeding time, it is almost impossible that the sick will arrive to the feeding site more early than the active. Besides, the same is true of speed. Thus, it is reasonable to use clustering method to classify chickens.

To verify the method, the repeated experiments of 24 chickens were conducted in this study. In the repeated experiments, data of 24 chickens were collected newly in another time. And through calculation with the same characteristic model, the values of characteristics were obtained, as shown in Table 5.

Table 5 Characteristic data and result of the repeated experiment

RFID	Ability to snatch food	Weight/kg	Moving speed/m·s^{-1}	The resting time/s	Standard Weight	Result of clustering	Result of farm classification
03190001	0.675	2.504	0.395	13.300	2.46	3	2
03190002	0.250	2.932	0.625	1.500	3.01	2	2
03190004	0.560	1.576	0.487	6.113	1.62	1	1
04160001	0.633	2.178	0.678	2.000	2.00	2	2
070B0019	0.425	2.784	0.221	10.667	2.90	3	3
070B001B	0.450	2.492	1.000	2.650	2.47	2	2
090A0033	0.460	1.547	0.217	8.553	1.52	1	1
090A0037	0.500	2.320	0.571	1.700	2.15	2	2
090A0040	0.425	1.583	0.140	10.926	1.46	1	1
090A0042	0.900	1.490	0.258	4.602	1.48	1	1
090A0043	0.550	1.860	0.333	2.308	1.83	1	1
090A0048	0.300	2.056	0.126	2.035	1.83	1	1
090A004A	0.725	1.435	0.132	11.808	1.54	1	1
090A004B	0.533	1.978	0.282	4.500	1.84	2	2
090A0050	0.575	2.530	0.121	3.700	2.50	3	3
090A0051	0.650	2.037	0.294	6.491	1.80	1	1
090A0055	0.700	1.513	0.377	8.538	1.74	1	1
090A0057	0.575	1.809	0.180	2.249	1.59	1	1
090A0058	0.450	1.939	0.347	4.776	2.01	1	1
090A0059	0.375	1.706	0.156	2.798	1.60	1	1
090A005D	0.350	1.299	0.800	4.444	1.45	2	1
070A0061	0.300	2.340	0.013	20.643	2.32	3	3
090A0047	0.353	2.428	0.013	18.510	2.30	3	3
090A0063	0.348	2.447	0.014	16.039	2.40	3	3

(1) Consistency between two repeated experiments

As can be seen from Table 6, most of the results are consistent except 03190001, 090A004B, 090A005D. The consistency rate is 87.5%. That means the collection and the results are not made by accident.

Table 6 Results of the repeated experiment

RFID	Result of first experiment	Result of second experiment	Result of farm classification
03190001	2	3	2
03190002	2	2	2
03190004	1	1	1
04160001	2	2	2
070B0019	3	3	3
070B001B	2	2	2
090A0033	1	1	1
090A0037	2	2	2
090A0040	1	1	1
090A0042	1	1	1
090A0043	1	1	1
090A0048	1	1	1
090A004A	1	1	1
090A004B	1	2	2
090A0050	3	3	3
090A0051	1	1	1
090A0055	1	1	1
090A0057	1	1	1
090A0058	1	1	1
090A0059	1	1	1
090A005D	1	2	1
070A0061	3	3	3
090A0047	3	3	3
090A0063	3	3	3

(2) Consistency between system clustering and farm classification

As seen from Table 6, the consistency ratio between the first experiment and farm classification is 96%. And it is 92% in the second experiment because of 03190001 and 090A005D.

In all, the method in this study can assist manual monitoring in large scale chicken farm usefully. The system can detect sick chickens in time and assist the chicken classification. But it still needs large scale experiment for further study if applied to scale farming.

4 Conclusions

The wireless network with the RFID-tag-collectors and weight sensors were adopted in this system for monitoring animals in the farm. Experiments show that the proposed system's identification results are in accord with the farm classification. The method in this study can assist manual monitoring in a large-scale chicken farm usefully. The system can detect sick chickens in time and assist the chicken classification. The unique features of this system are as follows:

(1) Online monitoring poultry epidemic from the perspective of poultry behavior.

Precise husbandry and epidemic warning based on information have always been highly discussed. As a result, this project further studied the poultry epidemic warning in the perspective of poultry behavior monitoring.

(2) Increased response speed of poultry epidemic monitoring

The project collects poultry behavior information online through farming IoT. And with the help of cloud computing technology, the epidemic warning system becomes much more responsive.

(3) Device reliability, low cost, practical

Compared with the conventional wireless sensor nodes for monitoring poultry behaviors, this system uses simpler and cheaper sensors including the RFID-tag-collectors and the weight sensor. To successfully collect the behavior information of an animal, only a RFID-tag needs to be attached on its ear or wore on its foot. As a result, the cost will be much lower and the pollution can be better avoided.

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