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# Study on Ruminant Recognition of Cows Based on Activity Data and Long Short-Term Memory Network

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**Abstract.** In this paper, the collected activity data with ruminating status label is used as the data set, based on the long short-term memory network in the recurrent neural network, in order to identify and judge the ruminating process of dairy cows. This paper analyzes the advantages of selecting activity data as input data and long short-term memory network as core algorithm, introduces the hardware design and composition of the self-developed activity data acquisition system, and describes the characteristics of long short-term memory network structure. It is innovative to combine cow activity data with long short-term memory network to identify ruminating in the time period of cow activity data. The experimental results show that the long short-term memory network has different recognition effects on dairy cows of different individuals through the learning of activity data, and the accuracy of ruminating recognition of the whole data is 0.78. This method is effective and feasible. It can provide ideas for the related research of intelligent animal husbandry.

**Keywords:** Rumination of cows · Activity data · Long Short-Term memory

## 1 Introduction

Today, the total number of dairy cows in China is about 13.766 million, and the total annual raw milk production is about 38.5 million tons, ranking third in the world [1]. Since 2010, in order to improve the hygienic quality and breeding efficiency of milk, large-scale dairy farming has been carried out in China. In the past, family farms with only a few dozen cows were gradually replaced by large-scale farms with 500, 000 cows. The main production tasks in large-scale pastures are cow feeding, milk production (milking), cow reproduction (estrus monitoring) and disease prevention. With the significant increase in the number of dairy cows in the pasture, the workload in farm production has been increased. It is basically impossible to complete these tasks manually, and there is an urgent need to use mechanization and information means to replace them.


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Ruminating activity is very important to the metabolic activity of dairy cows, and it is an important detection index in the process of disease prevention and supervision of dairy cows. Cow ruminating stimulates the secretion of saliva and digestive enzymes, which ensures the activity of rumen cellulose decomposition. Lack of related enzymes, cows will have symptoms such as indigestion, acidosis, limb ulceration, poor state, and finally lead to death. When there was ruminating disorder, the dairy cows showed that the number of ruminating decreased, the duration of ruminating was short or delayed, and even stopped ruminating [2].

Ruminating time is an important index to reflect the health of ruminants. The rhythm and time of ruminants are closely related to health status. Through the collection, processing and analysis of ruminant signals, ruminant health status can be more accurately detected and found. If there is a sudden decline in ruminant activity compared to the normal level, it indicates that the animal loses appetite or is sick, and long-term loss of appetite is a sign that the animal is in a state of disease. As long as there is no change in the health of daily feeding, pasture feeding and ruminants, ruminant activity is in a very stable state. When there are problems with feeding and breeding, the ruminating of the herd will change accordingly. For farm workers, early information on potential health problems of ruminants can be diagnosed and treated as soon as possible to recover losses for pastures. Therefore, the application prospect of cow ruminant recognition is very broad.

In the research of behavior recognition algorithm, Paula Martiskainen et al. (2012) studied a SAAR (Semantic Annotation and Activity Recognition) system, which uses SVM (Support Vector Machine) support vector machine technology to identify the three-axis acceleration of dairy cows [3]. M. Alsaaod et al. (2015) collected the motion information of dairy cows through pedometer, and developed a new RumiWatch algorithm to judge cow behavior, which is used to improve the automatic feeding and management system of dairy cows [4]. Jorge A. V á zquez Diosdado et al. (2015) developed a decision tree algorithm, which uses a three-axis accelerometer installed from the neck of a cow to collect data to classify cow behavior and detect the transition between lying and standing behavior [5]. C Arcidiacono et al. (2016) defined and implemented a new open source algorithm, using statistically defined thresholds to calculate cow steps to improve cow health benefits [6]; Md. Sumon Shahriar et al. (2016) used unsupervised learning method to study the dairy cow fever event detection system based on animal sensor, and used K-means algorithm to group the time series segmentation window to improve the observation sensitivity of dairy cow fever event [7].

Reith et al. (2012) [8] studied the relationship between daily ruminating time and estrus in four dairy farms. The HR-Tag system was used to record 349 estrous cycles of 279 dairy cows. Finally, the milk production data and reproduction data of 265 estrous cycles of 224 dairy cows were used for statistical analysis. The mixed mathematical model of SAS software was used to analyze the relationship between ruminating time and estrus. The experiment showed that 94% of the cows were related to the decrease of ruminating time. Chung et al. (2013) [9] proposed a data mining algorithm for cow estrus detection. In this algorithm, the Mel frequency cepstrum coefficient is extracted from cow sound, and the support vector data description method (SVDD) is used to realize early anomaly monitoring. Daniel. of the University of Minnesota in 2015. A.N.

et al. [10] the ruminating behavior of dairy cows with uterine diseases and metabolic diseases was studied by using the ruminating remote recorder of Israeli company, and it was found that the ruminating behavior of diseased dairy cows decreased greatly. it provides a theoretical basis for the effect of rumination on the health status of dairy cows. G á sp á rdy et al. [11] by monitoring the daily ruminating behavior and actual body weight of 96 dairy cows, it was proved that the ruminating behavior of dairy cows is an important factor affecting the health status and production performance of dairy cows. Clark (2015) et al. [12] by monitoring the hourly activity and ruminating data of each cow by wearing Israeli-produced SCR HR LD Tags for 27 cows and fitting them with a linear mixed model, it was determined that the ruminating behavior and activity of dairy cows were the predictive indexes of calving behavior of dairy cows. Kaufman et al. (2016) [13] the SCR ruminant collar was used to monitor the ruminating behavior of dairy cows 24 h a day to verify the relationship between ruminating time and subclinical ketosis. It is concluded that monitoring the ruminating time of dairy cows can identify the risk of subclinical ketosis in multiple dairy cows after calving.

The activity data of dairy cows refers to the data containing all kinds of behaviors of dairy cows, including feeding, ruminating, running, fighting with other cattle and so on. We use a wearable collector designed by ourselves to fix the collector on the neck of the cow to extract the activity data of the cow. Other data commonly used in cow ruminating research are sound data, body temperature data, video surveillance data and so on, of which the most commonly used is sound data, which is usually due to the complex composition of noise in the environment. Sound feature extraction requires a combination of multiple algorithms, so it is difficult to strike a balance between algorithm optimization and recognition accuracy. Because of the large amount of data and random cow activity, high-definition video data is difficult to achieve automatic identification, so it is generally used for manual observation to verify the recognition results of other data; compared with audio data and high-frequency video data, activity data not only contains rich motion information, but also a small amount of data is easy to train in the deep network after preprocessing. Therefore, we choose the activity data as the data of cow ruminant recognition research.

After extracting the activity data of dairy cows, it is necessary to select an appropriate neural network model to analyze and identify the activity data. Ruminating refers to the physiological activity in which some animals return semi-digested food from their stomach to their mouth and chew again after eating for a period of time [14]. Generally, the ruminating lasts for 40 min and 50 min at a time. Although the time sequence correlation of cow rumination is not the same as the stock price problem, compared with the classical cat and dog classification problem, cow rumination has a certain time series relationship, assuming that the proposed minimum time measure is one minute. then if the judgment of this minute is ruminating, the next minute probability is still ruminating, so we use the long short-term memory (LSTM) model of recurrent neural network as the core algorithm. Recurrent neural network is a kind of neural network which takes sequence data as input, recurses in the evolution direction of sequence and all cells are connected by chain [15]. Recurrent neural network has the characteristics of memory, parameter sharing and Turing completeness, so it is most suitable to make prediction according to the input time series. In the recurrent neural network, the long short-term memory network is the most common neural network. Compared with the ordinary recurrent neural network, the long short-term memory networks can solve the problem of gradient disappearance to a certain extent [16]. Based on the above discussion, we choose the long short-term memory network as the algorithm model of cows ruminant recognition.

## 2 Data Collection and Simple Processing

### 2.1 Data Collection System

The activity collection system mainly includes three parts: the activity collector, the base station and the host computer (PC). As shown in Fig. 1.

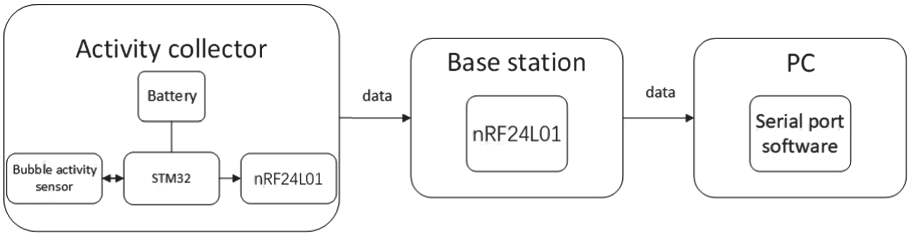


**Fig. 1.** Activity data collection system

**Activity Collector**
When ruminating, the cow will retch the food ball directly up to the mouth, chew carefully in the mouth, and then swallow back to the stomach, this process is repeated. There was a continuous fluctuation in the neck of the cow during the whole ruminating process, and the ruminating condition was determined by detecting the fluctuation. The activity collector is worn in the form of a collar on the neck of the cow, which is used to collect the activity data of the cows in real time. As shown in Fig. 2.

The collector consists of a microcontroller, a bubble activity sensor, a wireless transceiver module and a battery. The microcontroller is an ultra-low power 32-bit processor STM32L151C8T6, based on the ARM Cortex-M3 core. It has a data bus width of 32bit and a working power supply voltage of 1.65 V-3.6 V [17]. It has the characteristics of ultra-low power consumption and can meet the needs of products that have been used for a long time. The wireless transceiver module is a monolithic wireless transceiver chip nRF24L01 of 2.4 GHz to 2.5 GHz ISM band produced by Nordic Company. nRF24L01 connected to MCU, through SPI interface has the characteristics of small size, low power consumption, communication radius of about 80 m, etc. [18], it can cover the test environment. The CTRL pin in the sensor is connected to the MCU timer output pin PA1; OUT pin is connected to the MCU modular (AD) sampling channel PA0 [19]. The reference voltage of the AD conversion is set to 3.3 V, the sampling frequency is set to 10 Hz, and the sampling precision is set to 12 bits.

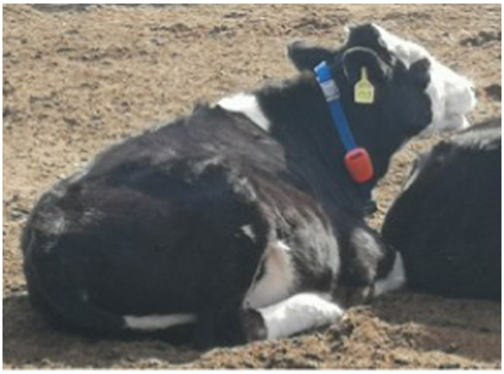

**Fig. 2.** A cow wearing an activity collector

Bubble sensor is a new type of ultra-low power consumption activity sensor based on the principle of liquid sloshing, which is composed of transparent cavity, infrared emitting diode and infrared receiving diode. The transparent cavity contains a certain amount of silicone oil and air (called bubbles). When the sensor shakes, the movement of the bubble causes the change of the medium between the infrared emitting diode and the receiving diode, which leads to the change of the induced current of the infrared receiving diode, so the movement trend is recorded as an electrical signal. The power consumption of the activity collector is only 1550.5 mAh per year. The two 2600 mAh lithium batteries can be used continuously for 6.87 years in ideal condition, which can meet the use conditions of the collector.

**Base Station and PC**

The base station includes the nRF24L01 wireless transceiver module, whose main function is to receive the data sent by the activity collector, connect the host computer through the serial port and send the data to the host computer. The host computer has serial port receiving software to receive the data sent by the base station. In the whole process of data acquisition from the activity collector to the host computer, the transmission rate is 8 pieces of data per second.

## 2.2 Labeling

When collecting the activity data of dairy cows, it is necessary to calibrate the real-time ruminating of dairy cows as a comparison of the results of subsequent model recognition. At present, the more commonly used method is to shoot through the live camera and analyze the video to get the ruminating state of the cow when collecting data. However, this method has some disadvantages, such as too high requirements for hardware, and may not be able to accurately track and observe an individual. Considering the field environment, we adopt the method of manually calibrating the collected data through manual observation in the field. The calibrated state is ruminant and non-ruminant state, non-ruminant state is calibrated to 0, ruminant state is calibrated to 1. We want the time to identify the results to be accurate to minutes, so when labeling, the minimum length of time is one minute.

We collected a total of more than 50 h of data from 6 cows, and finally selected about 40 h of data as the data set, considering the integrity of the data and labels.

## 2.3 Simple Processing

After obtaining the activity data, simple data processing and analysis are needed for follow-up work. We use matlab2016a to draw a graph of each minute's data to find the difference between ruminant and non-ruminant. As shown in Figs. 3 and 4. The two pictures are the data curves of ruminating and non-ruminating of the same cow, and the time is one minute. Figure 3 is the data curve of ruminating, and Fig. 4 is the data curve of non-ruminating. It can be seen from the picture that when cows do not ruminate, their activity data remain in a steady trend with little fluctuation. When ruminating, the activity data fluctuated greatly, which was obviously different from that

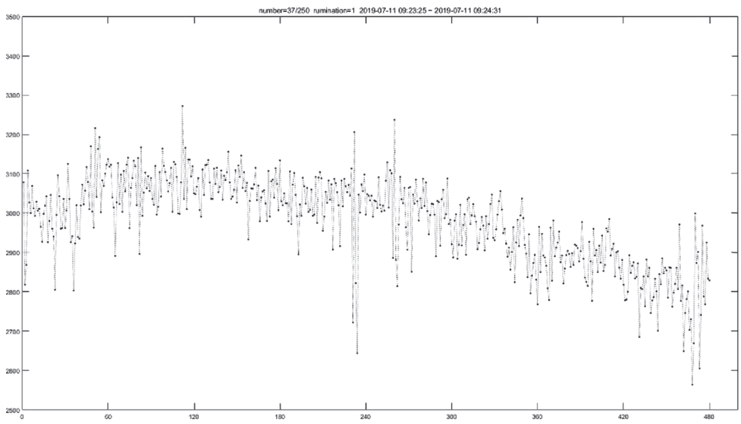


**Fig. 3.** Ruminant data curve

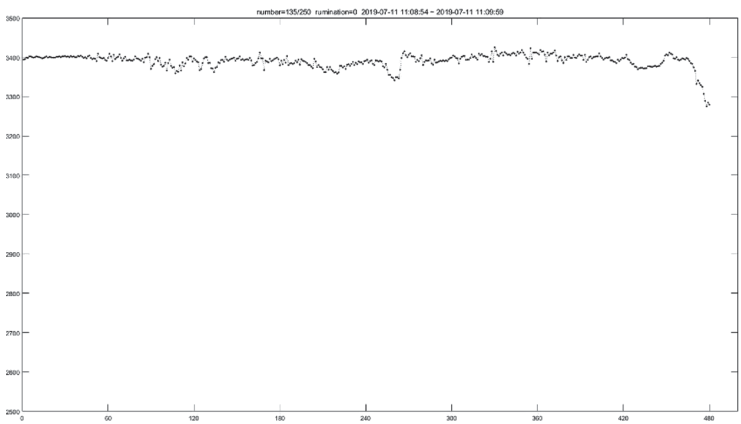


**Fig. 4.** Non-Ruminant data curve

of non-ruminating. This is because cows do not have too much vibration in their neck when they are not ruminating and eating, so the data extracted by the activity collector fluctuates more smoothly. When it ruminates and chews, the neck vibration is large, which is reflected in the large fluctuation of the data.

## 3 Long Short-Term Memory Network

Traditional recurrent neural networks are affected by short-term memory. If a sequence is long enough, it will be difficult for them to transfer information from an earlier time step to a later time step. Therefore, if you want to try to process a piece of text for prediction, the recurrent neural network may miss important information from the beginning.

During the period of back propagation, the recurrent neural network will face the problem of gradient disappearance. The gradient is used to update the weight value of the neural network. The vanishing gradient problem means that when the gradient propagates over time, the gradient will decrease. If the gradient value becomes very small, it will not continue to learn. One of the key points of recurrent neural network is that they can be used to connect previous information to the current task, such as using past video clips to infer the understanding of the current segment. If recurrent neural network can do this, they become very useful, but traditional recurrent neural network has long-term dependence problems. As an effective method to solve the long-term dependence problem of general recurrent neural network, long short-term memory network is widely used.

The standard neural network is divided into three layers: input layer, hidden layer and output layer. Input layer can get the data from our custom variables, perform matrix operations on the data, apply it to the activation function, and then store the results in the variables. Hidden layer can get the data from the variables output from the input layer, and after calculating and using the activation function, output the results to the variable for the next hidden layer to use. This process will be iterated several times according to the number of hidden layers you defined. In output layer, the data is obtained from the output variables of the last hidden layer, and the corresponding number of output results are obtained according to the need after operation and using the activation function.

As shown in Fig. 5, the input layer has a cell for reading and transmitting activity data. There are two hidden layers, the number of cells in each layer is 10, the weights of cells between the hidden layers can be transmitted to each other. And the output layer has two cells, representing 0 and 1 respectively. In the long short-term memory network, the core is a hidden neural layer cell, including various gate parameters and activation functions, before and after the cell, each needs input and output network layer. The hidden layer contains three gates for the realization of memory– the forgetting gate, the input gate and the output gate.

### 3.1 Forgetting Gate

The forgetting gate can decide which information should be discarded or retained. The information from the previously hidden state and the current input are entered into the Sigmoid function at the same time, the output value is between 0 and 1, the closer to 0

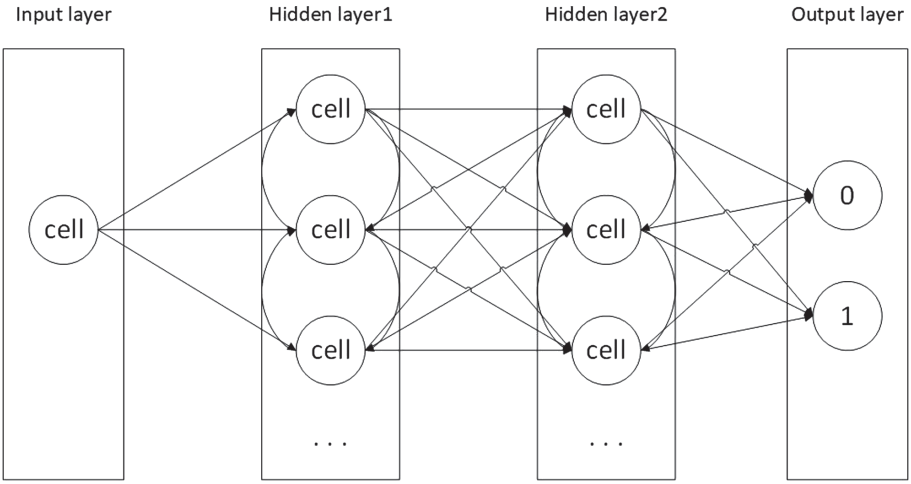


**Fig. 5.** LSTM structure

means the more should be forgotten, and the closer to 1 means that the more should be retained.

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

The calculation of the forgetting gate is shown in formula (1). $h_{t-1}$ is the hidden layer output of the last moment, $x_t$ is the input value of this moment, $W_f$ is the weight matrix of the amnesia gate, $b_f$ is the biases value of the forgetting gate, σ represents the sigmoid function, and $f_t$ represents the output of the forgetting gate.

### 3.2 Input Gate

The input gate is used to update the cell status. Firstly, the information of the hidden state of the previous layer and the information of the current input are passed to the sigmoid function. Adjust the value to between 0 and 1 to determine which information to update. 0 means unimportant, 1 means important.

Secondly, the information of the hidden state of the previous layer and the information of the current input are passed to the tanh function to create a new candidate vector. Finally, the output value of sigmoid is multiplied by the output value of tanh, and the output value of sigmoid determines which information in the output value of tanh is important and needs to be retained.

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

$$C_t^{'} = \tanh\left(W_c\left[h_{t-1}, x_t\right] + b_c\right) \tag{3}$$

In formula (2), $W_i$ and $b_i$ represent the weights matrix and biases value of the input gate respectively, and the output of the input gate can be obtained at this time. In formula

(3), $W_c$ and $b_c$ represent the weight matrix and biases value of neurons respectively. Through the operation of tanh activation function, the value of an intermediate state of cell output can be obtained.

$$C_t = f_t * C_{t-1} + i_t * C_t^{'} \tag{4}$$

The output of the forgetting gate at this time is multiplied by the output of the cell at the previous moment. Then the product of the intermediate state of the input gate and the output of the cell is calculated. And the two parts are added, that is, the output of the cell at that time, as shown in formula (4).

## 3.3 Output Gate

The output gate is used to determine the value of the next hidden state, which contains the previously entered information. Firstly, the previous hidden state and the current input are passed to the Sigmoid function. Secondly, the newly obtained unit state is passed to the Tanh function. Thirdly, the Tanh output and the Sigmoid output are multiplied to determine the information that the hidden state should carry. Finally, the hidden state is taken as the current unit output, and the new unit state and the new hidden state are transferred to the next time step.

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

In formula (5), $W_o$ and $b_o$ represent the weights matrix and biases value of the output gate, and the output at this time can be obtained by calculation. Then the output of the hidden layer is calculated by formula (6).

## 3.4 Activation Function

If there is no activation function in the neural network, then the output of each layer is a linear function of the upper input. It is easy to know that no matter how many layers there are in the neural network, the output is a linear combination of input, which has the same effect as no hidden layer. It makes the hidden layer meaningless. After introducing the nonlinear function as the excitation function, the neural network is no longer a linear combination of input and can approach any function. The activation function Tanh is a commonly used nonlinear activation function, which is used to help adjust the value of flow through the network. The tanh function always limits the value to between $-1$ and 1. The mathematical definition of the tanh function is shown in formula (7) (Figs. 6 and 7).

$$\text{tanhx} = \text{sinhx}/\text{coshx} \tag{7}$$

The sigmoid function, also known as the Logistic function, is used to calculate the output of cells in the hidden layer. Because it can map a real number to an interval of 0 to 1, it can be used for binary classification. The effect is better when the feature difference is more complex or the difference is not very large. As an activation function, Sigmoid has many advantages, such as smooth, easy to derive, very good symmetry, insensitive to input beyond a certain range, and so on.

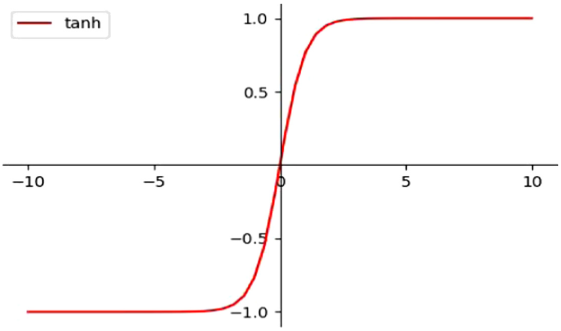


**Fig. 6.** Tanh activation function graph

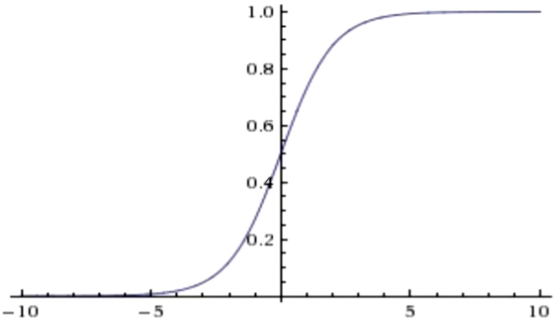


**Fig. 7.** Sigmoid activation function graph

# 4 Experiment and Result Analysis

## 4.1 Experimental Environment

The data collection site was selected from a cattle farm in a village in Hohhot, Inner Mongolia Autonomous Region, in July 2019. A total of about 40 h of activity data of six cattle were collected, with a total of more than 1 million data.

The design language is Python, and its version is 3.6.4. Tensorflow version is 1.13.1.

The initial learning rate is set to 0.0005, and the batch size and time step are both 480. If the learning rate is too large, it will lead to the problem that the possible loss function does not converge; the batch size and time step are set to 480 because the minimum length of manual labels is one minute, while the amount of data in one minute is 480.

## 4.2 Dataset Partition

The data collected each time is saved in the txt documents, which include year, month, day, hour, minute, second, activity data and manual labels. The minimum time length of manual labels is one minute, ruminating state is labeled as 1, non-ruminating state is labeled as 0, and the ratio of 0 and 1 in all data labels is about 7:3. As the duration of the data collected in each activity is different, in order to make it more convenient for the model to read the data, the data collected in the first three hours are fed into the model, and the data more than three hours in every document are discarded. In order to prevent the over-fitting of the model to a single individual, six Holstein cows were selected, and the amount of data of each cow was also different, ranging from 3 h to 12 h.

We send the data of the first three hours of each txt document into the model one by one, in which there are 57600 pieces of data in the first two hours as the train data set and 28400 pieces of data in the third hour as the test data set. So that the ratio of the train data set to the test data set is 2:1, which is close to the standard proportion of 7:3, and the partition is reasonable. The training effect is measured by the value of loss function, and the test effect is measured by the accuracy.

### 4.3 Experimental Results

The loss function is also called the cost function, which is the objective function of neural network optimization. The process of neural network training or optimization is the process of minimizing the loss function. The smaller the value of the loss function is, the closer the predicted result is to the real result. The effect of the neural network model and the goal of optimization are defined by the loss function. The loss function between the expected value and the real value can be obtained by calculating the cross entropy. Then the regularization loss of the model is calculated. The total loss is equal to the sum of regularization loss and cross-entropy loss. The expected effect is that the loss function decreases gradually with the increase of the number of iterations. As shown in Fig. 8.

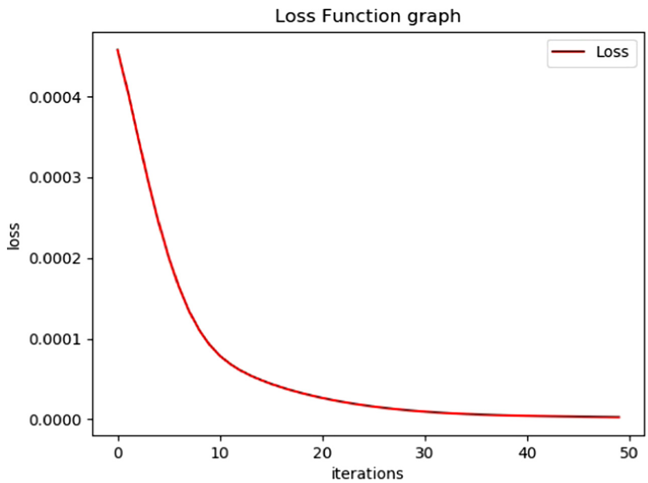


**Fig. 8.** Loss function graph

The document data of different individuals are identified and determined, and the result is shown in Table 1.

**Table 1.** The accuracy of different individuals

| Number of cows | Duration of data/hours | Accuracy |
|---|---|---|
| 01 | 6 | 0.70 |
| 02 | 6 | 0.73 |
| 03 | 9 | 0.80 |
| 04 | 12 | 0.73 |
| 05 | 3 | 0.94 |
| 06 | 6 | 0.78 |

In Table 1, the duration of the data of the six cows varies, depending on the status of the data we collected at that time and the integrity of the data obtained. We believe that the activity data of different individuals are different, which leads to different recognition effects of long short-term memory networks. Table 2 contains some mathematical eigenvalues of dairy cows activity data.

**Table 2.** Mathematical eigenvalues of different individuals

| Number of cows | Average | Max | Min |
|---|---|---|---|
| 01 | 3110 | 3511 | 1602 |
| 02 | 3064 | 3689 | 1531 |
| 03 | 2998 | 3497 | 1551 |
| 04 | 3188 | 3717 | 1488 |
| 05 | 2994 | 3619 | 1329 |
| 06 | 2947 | 3578 | 1551 |

As shown in Table 2, although there is little difference in the activity data values of different individuals, it is enough to affect the degree of recognition of the data by the neural network.

We believe that the neural network has different recognition results for different individuals, and the influencing factors include the difference of individual data value itself and the different duration of individual data, while the difference of individual data duration is actually the difference of the amount of data. Take No.05 cow with the best recognition effect as an example, compared with other individuals, its average value and maximum value are in a middle level, and its minimum value is the smallest of all individuals, which may be one of the influencing factors. The No.05 duration of data is the least among all individuals, and we think that this will more or less affect the recognition effect of the model. If No.05 has more activity data, will its accuracy of recognition be close to the level of other individuals? Unfortunately, due to environmental constraints, there is no more individual data No.05 to support this point. However, we select any three-hour data of other individuals, and the accuracy of recognition is lower than that of No.05. As shown in Table 3, we output the data of other individuals every three hours. Based on the comprehensive analysis of all individual data, it is concluded that the recognition accuracy of long short-term memory network is 0.78. We think this is an acceptable result.

**Table 3.** The accuracy of different individuals every three hours

| Number of cows | Accuracy |
|---|---|
| 01 | 0.68; 0.72 |
| 02 | 0.69; 0.77 |
| 03 | 0.92; 0.82; 0.67 |
| 04 | 0.71; 0.73; 0.76; 0.73 |
| 05 | 0.94 |
| 06 | 0.85; 0.71 |

## 5 Conclusion

The experimental results show that the activity data can also be used as the data set of cow ruminating recognition, and the long short-term memory network can effectively identify the activity data of dairy cows ruminating. Compared with sound data or video analysis, activity data is more convenient to extract, less noise, and can be effectively recognized by neural network, and get a more ideal effect.

Due to environmental limitations, this study can also be improved in some aspects. Later, we can continue to collect activity data, improve the data set, specifically, we can add more new individuals, expand the amount of data of all individuals, make the amount of data of all individuals sufficient and close, balance the proportion of 0, 1 labels, and so on.

From the analysis of experimental results, this study has a certain feasibility; from the practical analysis, this study combines cow activity data with long short-term memory network to provide reference ideas for intelligent animal husbandry.

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