Estrus Detection in Dairy Cows from Acceleration Data using Self-learning Classification Models

Ling Yin
College of Informatics, South China Agriculture University, Guangzhou,China
Email: yin_ling@scau.edu.cn

Tiansheng Hong and Caixing Liu
College of Engineering, South China Agriculture University, Guangzhou, China
Email: { tshong, liu}@scau.edu.cn

***Abstract*—Automatic estrus detection techniques in dairy cows have been present by different traits. Pedometers and accelerators are the most common sensor equipment. Most of the detection methods are associated with the supervised classification technique, which the training set becomes a crucial reference. The training set obtained by visual observation is subjective and time consuming. Another limitation of this approach is that it usually does not consider the factors affecting successful alerts, such as the discriminative figure, activity type of cows, the location and direction of the sensor node placed on the neck collar of a cow. This paper presents a novel estrus detection method that uses k-means clustering algorithm to create the training set online for each cow. And the training set is finally used to build an activity classification model by SVM. The activity index counted by the classification results in each sampling period can measure cow's activity variation for assessing the onset of estrus. The experimental results indicate that the peak of estrus time are higher than that of non-estrus time at least twice in the activity index curve, and it can enhance the sensitivity and significantly reduce the error rate.**

***Index Terms*—accelerometer, k-means, activity index, cow**

I. INTRODUCTION

Effective detection of estrus in cows has been widely studied in animal sciences. The high rates of detecting estrus can improve insemination results, and control calving interval and total pregnancy rate [1]. Methods of detecting estrus include two major categories. One is the manual measuring, e.g. changes in body temperature [2-3], changes in vaginal mucus resistance [3], visual observations made by a skilled farmer and based on his/her intuition and experience. However, these approaches are labor-intensive, time consuming [4], costly and inaccurate operation when dealing with a number of animals. The other is automatic monitoring. Various sensor systems have been reported for the detection of key events of cows (e.g. estrus, illness or welfare). Guo et al. uses the GPS, magnetometer and accelerometer to recognize the behaviors of cows[5]. Steve applies the electrocardiograph to determine cattle heart rate[6]. Van et al. and Jonsson et al. utilize pedometers attached to the legs or neck collar to record the cow's activity [7-8]. In recently, an efficient activity type classification model using 3-axes accelerometers attached to the cows' neck becomes a major method of estrus detection. Paolo and many researchers monitor and classify the behavior patterns of cows by accelerometers [8-12].

The behavior classification algorithms relied primarily on local statistics computed from acceleration to build object models by means of supervised techniques such as Support Vector Machines(SVMs)[10,13], Kalman filter and fuzzy logical. In this context, an accuracy training set creation approach is present for the first crucial step in the behavior classification algorithms, that is based on the view that cows' behavior are recorded by manual observation from video or in the barn directly, and this process is subjective, labor-intensive and requires good visibility of the cows. Furthermore, cows have different body sizes and respective activity patterns, which can be affected by the species group, environment, climate and other external factors. And the direction and location of sensor node attached may be distinct. The training set created by observation is not adapted to each cow. To automatically create more discriminative activity feature, k-means clustering algorithm is used to achieve the training set for each cow that can help to train an activity classification model with the SVM. The activity index is the statistical results of cows' movement in each sampling period, and its variation is used for assessing the onset of cow estrus in this paper.

II. HELPFUL HINTS

The study was conducted in the Wen's dairy company in Zhaoqing (Guangdong, China) from December 2010 to March 2011, which is the largest dairy company with the breeding area of about 2,000 acres and nearly 10,000 cows in Guangdong province. A total of 10 lactating Holstein cows were used as experimental animals and

doi:10.4304/jcp.8.10.2590-2597

kept in a free range housing cubicle. Four cows showed estrus during the experimental period.

A. Measurement System

The 3-axis accelerometer (ADXL330, Analog device, USA) with sensitivity between -3g to 3g is embedded in a wireless sensor node that is attached to neck collar of cows. The wireless sensor node also contains a ferroelectric flash (WQ8N25P, Huabang, Taiwan) with the capacity 24MB and a 2.4GHz transmitter module (CC2500, TI, USA). The acceleration is recorded and stored in the flash usually, and transmitted to the control center at the milking time everyday (i.e. twice a day). The wireless sensor node is encapsulated with a small waterproof box and a 2AA battery attached, measured 63mm×30mm×25 mm and weighed 40g.

B. Data Preprocessing

The acceleration is sampled at 10Hz frequency. The sliding neighborhood smooth method is used to eliminate the noise of the sampling data, which detects the adjacent four points, if a protruding value is found, instead of the mean value of the neighborhood values. The smooth data algorithm is used to get rid of the abnormal points.

Windowing technique divides the acceleration into small time segments (sliding window) before the application of classification algorithms. Seven variables are defined in each sliding window: average acceleration in each of three axes $(x_{avg}, y_{avg}, z_{avg})$, differential value in each of three axes $(x_{diff}, y_{diff}, z_{diff})$, sum of differential values sum_{diff}. The differential value shows the difference between the two adjacent sliding windows. Sum of differential value is calculated by the following equation:

$$sum_{diff} = |x_{diff}| + |y_{diff}| + |z_{diff}| \tag{1}$$

C. Classification Modeling

Cow behaviors can be classified into many sub-classes according to different standards and purposes, which may involve lying, standing, ruminating, grazing, drinking, walking, mounting and so on. Unlike the classification of specific behaviors, the increased level of cow activity can be used as a measurement for estrus detection. According to the four acceleration parameters, the cow's activities can be divided into three categories: lower activity, medium active and high activity. They do not mean any specific behavior, but describe the cow's activity level. The ratio of each activity type could be used as an indicator of the cow's restlessness [14-15].

2.3.1. Training set obtained by K-means clustering

K-means clustering algorithm [16, 27] is an unsupervised learning algorithm, used to classify the cow's activities based on the collected acceleration in a sliding time window. It determines the cluster center at every point by minimizing the squared error based objective function. Activity characteristics of cows can be mined by k-means clustering algorithm, and build the SVM training set.

K-means clustering is a method commonly used to automatically partition a data set into k groups. In this context, there are three clusters: lower activity, medium activity, high activity. In this application, the feature set X_p has four variables, which could be described as follows:

$$x_i = \{x_{diff}, y_{diff}, z_{diff}, sum_{diff}\} \tag{2}$$

The clustering algorithm is then described as below:

Step 1 - Initialization:

Select the first k data points as the cluster centers c_i for initialization.

Step 2 - Compute new points cluster:

For each data point x_p belonging to a cluster whose center has the shortest Euclidean distance to that point:

$$\|x_p - c_i(l)\| < \|x_p - c_j(l)\| \tag{3}$$

$i, j = 1,2,\cdots,k, i \neq j$, then $x_p \in s_i(l)$,

where $s_i(l)$ is the category with the center c_i after l iterations.

Step 3 - Calculate the new cluster centers:

Use all members of the newly created category to recalculate the cluster center. Each cluster center c_i minimizes the objective function J that is described as follows:

$$J_j = \sum_{x_\sigma \in S_j(l)} \|x_p - C_i(l+1)\|^2 \tag{4}$$

The new cluster centers $c_i(l+1)$ after $l+1$ iterations are calculated as:

$$C_i(l+1) = \frac{1}{N_j} \sum_{x_p \in S_j(l)} X_p \tag{5}$$

Step 4 - Check the convergence:

If the cluster centers no longer move, then convergence has been met; otherwise go back to Step 2 and continue the iteration.

$$c_i(l+1) = c_i(l) \tag{6}$$

After clustering by the k-means algorithm, the classified data set is used as the SVMs training set.

2.3.2. SVMs multi-classification model

Support Vector Machines (SVMs) are an efficient leaning classification method, proposed by Vapnik. The SVMs present good theoretical properties and behaviors in problems of binary classification [17]. In this application, multi-class support vector machine classifiers are used to measure three activity levels of cows.

Let $\{(x_1, y_1), \cdots (x_n, y_n)\}$ be the training set of SVMs, where x_i is an input vector of length n, and $y_i \in \{1 \cdots k\}$ denotes the output class. The binary SVM is to find a hyperplane and threshold (w,b) that separates the positive and negative examples with maximum margin, penalizing points inside the margin linearly in a user-selected regularization parameter c>0. The SVMs classification problem can be restated as finding an optimal solution to the following quadratic programming problem:

$$\min_{w \in \mathrm{H}, b \in R, \xi \in R^l} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i , \tag{7}$$

$$y_i((w \cdot x_i) + b) \geq 1 - \xi_i, i = 1,\cdots,n, \xi_i \geq 0.$$

where the hyperplane is $(y_i y_j K(x_i, x_i))_{k\times k}$,

$$y = (y_1, \cdots y_k)^T.$$

The kernel function selects the radial basis function:

$$k(x_i, x_j) = exp\left(-\gamma\|x_i - x_j\|^2\right) \tag{8}$$

The formula above is motivated by the fact that minimizing the norm of w is equivalent to maximizing the margin, and the goal of maximizing the margin is in turn motivated by attempts to bound the generalization error via structural risk minimization.

2.3.3 Statistical analysis

Acceleration in each sliding window is classified into different activity categories using the SVMs classification model. However, the classification of single data point cannot help to determine whether the cow is in estrus. It needs to count up the classified activity data to get the activity index of each cow. Many works show that the duration of a cow's estrus period lasts for roughly 12-16 hours with a range of 2-30 hours [1]. Therefore cows' classified activity data makes statistics in a hour time slice. If a cow's activity index beyond the normal status, it gives the estrus signal.

Here we select one hour as the slice time, and use the following formula to calculate activity level at t slice time:

$$l_t = \sum_{i=1}^{k} w_i s_i \tag{9}$$

where w_i is weight of the i-th category, s_i is the total number of the i-th category in a specific time slice, and k is the number of clusters. The activity index m_t consists of two parts:

$$m_t = \theta_t + \delta_t \tag{10}$$

where θ_t is the historical comparison value, that is the ratio of every slice time activity level to the average amount of the same time of three days before

$$\theta_t = \frac{3l_t - (l_{t-24} + l_{t-48} + l_{t-72})}{(l_{t-24} + l_{t-48} + l_{t-72})} \tag{11}$$

and δ_t is the increase or decrease trend, that counts the number of hours of activity continued to be increased or decreased

- $$\delta_t = \frac{l_t - l_{t-1}}{l_{t-1}} \tag{12}$$

III. RESULTS

A. Training Set by K-means

Our experiments calculated the four clustering features with different sliding window lengths in order to check whether it affects the clustering results. All acceleration features were computed respectively in the length of 10, 20 and 50 samples windows. The sampling rate is 10Hz and the duration of a sliding window could be 1, 2 or 5 seconds. We selected 24h time series of ten cows (6 in non-estrus and 4 in estrus) acceleration, and calculated the features in each sliding window to perform k-means clustering. Results of both estrus and non-estrus data sets are presented in Table 1, which show that cows are motionless about two-thirds of time. The medium active and high active significantly increase by 17.5% and 46.5% in estrus at 1s sliding windows, and the high active increases 48.1% and 44.1% respectively in 2s and 5s sliding windows. That is to say, the different length of a sliding window does not obviously affect the proportion of the high activity increment, but it will change the classification results. The longer sliding window is the higher proportion of high active and the lower proportion of lower activity. Cow movement rate changes slowly. The 1s sliding window cannot collect a complete cycle of action. Nielsen pointed out that a cow's walking period must last at least 5s[18]. Some slow action will be divided into lower activity state. However a longer sliding window will smooth the data and reduce the net static value, while the differential value of a longer sliding window will increase. Figure 1 shows a big set of acceleration already classified by the activities performed by a cow. Each graphic represents noncontiguous activities measures from a cow in three hours. In the lower activity graphic Fig. 1a, there is little variation in the 3-axis acceleration values. The z axis has a mean value near zero, meaning which is horizontal positioned axis. During this activity the cow is usually sitting, standing, or lying. Figure 1b corresponds to the acceleration measurements when the cow is medium active graphic, and there is a lower variation in the 3-axis acceleration values. During the high activity (Fig. 1c), the axes variation values are maximal. Three axes values are clearly distinguished as the cow performs the medium and lower activity activities.

B. K-means Cluster Center

This experiment data set is obtained from two cows (Node27 and Node28), consisting of 518400 data points and six consecutive days (in non-estrus) data samples. The k-means clustering results for Node27 data set are presented in Table 2, and those for Node28 are presented in Table 3. The cluster center in k-means algorithm is the center point of the cluster, which minimizes the sum over all data points. Each subset has a cluster center projection, and contains all data points whose projections are closer to this center's projection than to other centers' projections. Comparison of Table 2 and Table 3 illustrates that the cluster centers of Node27 are quite different from those of Node28. During the lower activity period, the cluster centers of zdiff values are observed from 0.12 to 0.31, which vary nearly 158%, and the other three parameter variations, sumdiff, xdiff, ydiff, reach 112%, 93.3% and 95.6%, respectively. There is a lower variation in cluster center value during the high activity period, and the maximal variation is 54.5% and the least is 11.4%. Moreover, the cluster center mean values of the two cows are significantly different. The parameter zdiff has the most variation is 82.7%, and the sumdiff varies 50.8%. On the other hand, seventy percent of Node28 data was randomly selected as the training data set, and all data points of Node27 were used as the test data set. The SVM classifier was trained with the results calculated by k-means cluster in Node28 acceleration data. This optimal classification model was tested on the Node27 data set. The final classification results with SVM are presented in the Table 4 that gives the number of data point in each activity type in column. The rows show the k-means clustering results. The percentages of classified activity type by SVM and by k-means are given in diagonal. For LA activity type, SVM and k-means take 50.7 and 73.0%, respectively, and 22.3% LA are misclassified as MA. The same case also exists in HA and MA. This can be explained as that the average values of acceleration parameters of the Node27 cow are significantly higher than the Node28 cow. In that case the Node28 cow tends to be inactive while the Node27 cow performs more active. However the SVM results leads to the false determination that Node27 cow is in estrus. When using the Node27 data as training set to build the SVM classification model and test the Node28 data, we get Table 5, which gives the same type explanation.

C. Activity Index Analyses

The activity index measures how much the cow has moved in each sampling period. The numbers of the three classified activity categories are used for assessing activity index in this paper. Lower activity denotes the almost stationary state and medium activity denotes slight movement from Figure 1. Indicators of estrus include the increased restlessness, and the increased activity[19]. The high activity in the estrus period has significantly increased more than in non-estrus period. The weight of each category is estimated in the experiments and takes value from {0, 0.1, 0.9}. Figure 2 illustrates, for each hour interval, the activity index curve of an estrus cow. The day0 represents the last 24h period before the onset of estrus, 4 days before the estrus and 10 days after the day0. The activity index curve indicates that the cow has regular activity peak and trough of a day. In non-estrus time the index values are typically between -5 and 5; but in estrus time the activity index increases significantly to 15, which is three times than the usual value. This method can generally determine the estrus behavior from the beginning of restless to 6 hours after.

TABLE 1
EACH ACTIVITY PERCENTAGE OF THE TOTAL ACTIVITY AFTER K-MEANS CLUSTERING IN ESTRUM AND DIESTRUM DATA SETS(24H TIME SERIES) (MEAN ±S.D.). COLUMNS SHOW THE LOWER ACTIVITY (SL), MEDIUM ACTIVITY (MA), HIGH ACTIVITY (HA), AND THE ROWS SHOW THE LENGTH OF A SLIDING WINDOW (SW).

SW	Non-estrus (%)			Estrus (%)		
	SL	MA	HA	SL	MA	HA
1s	70.9±3.3	20.5±2.6	8.6±0.5	63.3±2.6	24.1±2.7	12.6±0.2
2s	67.5±3.6	22.3±3.1	10.2±4.3	59.0±3.1	25.9±4.4	15.1±1.2
5s	60.1±4.9	25.6±3.7	14.3±1.2	50.7±2.8	28.7±2.6	20.6±2.4

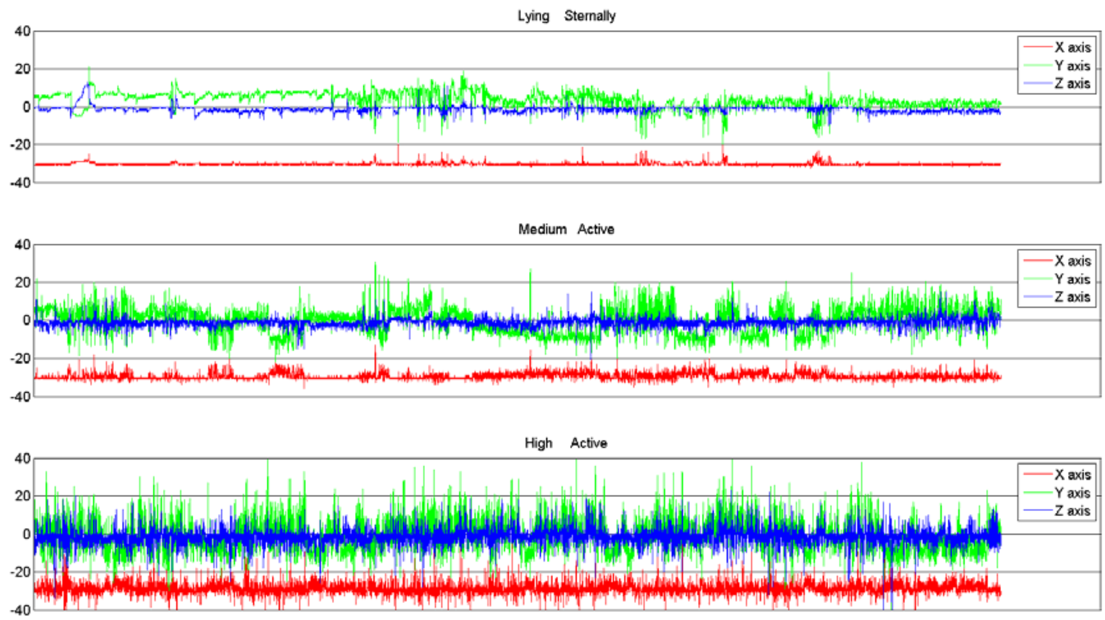


Fig.1. Three axis acceleration classified by activity type. The acceleration variation is little during the lower activity (a). During the medium activity period, the cow performs a lower variation. When the cow has highly active (c), there is a high variation in the three axes values.

TABLE 2
CLUSTERING CENTER OF NODE27 COW

	sum_{diff}	x_{diff}	y_{diff}	z_{diff}
LA	1.06±1.00	0.29±0.49	0.45±0.62	0.31±0.53
MA	6.04±1.86	1.48±1.15	2.55±1.64	2.01±1.52
HA	15.78±6.48	3.78±3.03	6.67±4.1	5.33±4.11
mean	2.91	0.73	1.23	0.95

TABLE. 3
CLUSTERING CENTER OF NODE28 COW

	sum_{diff}	x_{diff}	y_{diff}	z_{diff}
LA	0.50±0.50	0.15±0.36	0.23±0.42	0.12±0.32
MA	3.17±1.46	0.86±0.75	1.44±1.11	0.87±0.86
HA	12.27±5.92	2.84±2.27	5.99±3.99	3.45±3.16
mean	1.93	0.51	0.90	0.52

TABLE 4.

COMPARISON OF THE PREDICTION RESULT WITH SVM MODEL TRAINED BY NODE28 DATA SET AND THE CLUSTERING RESULTS WITH K-MEANS ALGORITHM IN NODE27. ROWS REPRESENT THE RESULTS OF CLUSTERING, AND COLUMNS GIVE THE PREDICTIVE VALUES BY SVM THAT CONSTRUCTED WITH THE TRAINING SET OBTAINED BY NODE28.

	LA	HA	MA	K-means	Percentage (%)
LA	262652	115662	0	378314	73.0
MA	0	86709	26476	113185	21.8
HA	0	0	26880	26880	5.2
SVMs	262652	202371	53356	518379	1
Percentage (%)	50.7	39.1	10.3	1	

TABLE5.

COMPARISON OF THE PREDICTION RESULT WITH SVM MODEL TRAINED BY NODE28 DATA SET AND THE CLUSTERING RESULTS WITH K-MEANS ALGORITHM IN NODE28. ROWS REPRESENT THE RESULTS OF CLUSTERING, AND COLUMNS GIVE THE PREDICTIVE VALUES BY SVM THAT CONSTRUCTED WITH THE TRAINING SET OBTAINED BY NODE27.

	LA	HA	MA	Total	Percentage (%)
LA	321889	0	0	321889	62.1
MA	119069	53644	0	172713	33.3
HA	0	12373	11425	23798	4.6
Total	440958	66017	11425	518400	1
Percentage (%)	85.1	12.7	2.2	1	

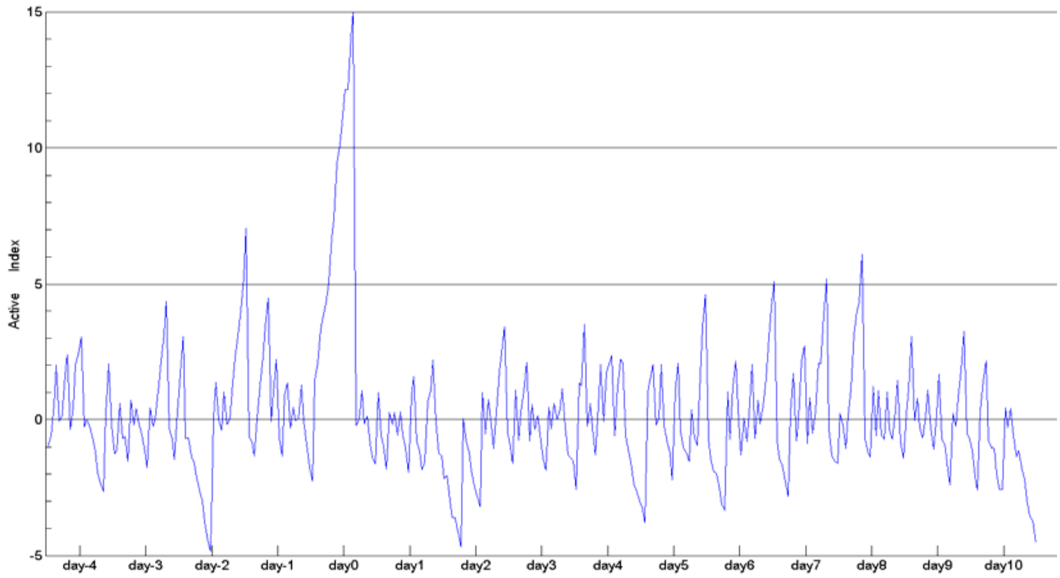


Fig. 2. Activity index curve per hour from 4 days before the onset of estrus(day0) to 10 days after. Day0 is the onset of estrus day, and day-1 is the day before the estrus day, day1 is the day after the estrus day.

IV. Discussion

Previous estrus detection research with the electronic technologies achieved sensitivity up to 94% and an error ratio of 53% [20]. Many studies reported some factors affecting successful automatic estrus detection. Løvendahl et al. pointed out that rates of estrus detection and error rate depend on the chosen threshold level [21]. Roelofs et al. showed s that expression of estrus can be influenced by many factors, such as heritability, number of days of postpartum, lactation number, milk production, health and external environmental factors like season, body size, housing and etc [22]. Wilhelm et al. who studied estrus detection using the ANN and MARS, obtained the sensitivity over 85%, and showed that the average calving interval and cow body condition index are the most important variables determining the estrus detection result [23]. Estrus intensity was detailed observations of 67 females performed by Emanuel et al. that showed more heifers than cows exhibit a strong standing estrus [24]. Synchronism and subsequent generation of sexually active groups led to an increased rate of false-positives in a study by Holman et al. [25]. López-Gatius et al. [26] analyzed the data obtained from 5883 cows to evaluate that factors such as lactation and insemination number, season and so on contribute intensely to the walking activity at estrus. Our experiments show that the acceleration data of individual cows varies widely. Stricter thresholds or constant parameters model will lead to false detection. There are many factors affecting estrus intensity: cow age, cow body condition, season, health problems. Because the direction and location the sensor node attached to the neck of each cow is uncertain and battery voltage fluctuates, which will impact greatly on the acceleration [28].

For the comparison of three different length sliding windows over a 24h period in the experiments, the activity index is determined by the change ratio of HA, and the length of the sliding window does not affect the result of detection. The experiment results also show that cows in estrus period become restless, their high activity significantly increases.

Since cows have different physical activities in different time every day, the activity index considers the comparison of their activity changes with those in the same time three days before. Activity index will accumulate the increased activity in the continuous estrus period. Our experiment results have shown that the peak of estrus time is higher than that of non-estrus time at least twice, which has very good estrus detection ratios and low false detection ratios.

V. Conclusion

This paper introduced a self-learning algorithm to estimate cows' activity index to detect estrus. The k-means cluster is used to investigate the statistical acceleration variation and establish the training set online, which makes it possible to adapt to individual activity of cows. The training set obtained by k-means clustering algorithm is used to build the activity classification model with SVMs algorithm. The statistical activity index based on the results of activity classification per hour is designed. Estrus detection is measured when the activity index is investigated a peak value in excess of normal value of 2 times above. Our method can accurately detect the estrus in experiments on 10 cows (4 estrus) and the number of false positives is zero (6 non-estrus). Considering that the experiments were conducted only in a small range, this estrus detection method may be more preferable to various conditions on different cows, and can enhance the sensitivity and significantly reduce the error rate. In addition, the method does not require accurate behavior classification of a cow, thus it doesn't require video recording or manual observation of cows.

ACKNOWLEDGEMENTS

The project was supported by the Chinese National High Technology Research and Development Program (No. 2006AA10Z246) and the earmarked fund for China Agriculture Research System (CARS-27), the City Science and Technology Research Program of China under Grant No.11C42100769, the Industry-Education-Research Cooperation Project of Guangdong Province and Ministry of Education under Grant No. 2011A090200072, the Science and Technology Planning Projects of Guangdong Province under Grant No. 2012A020602102 and No.2010B020315024, the innovative cultivate projects for university outstanding young in Guangdong Province in 2012 and No. 2012LYM_0032. Special Fund of Guangdong Province to support the development of agricultural mechanization in 2012. The National Spark Project in 2012 and No.2012GA780062. We specially thank Zhaoqing Dinghu Wen's Dairy Ltd. Co. for their assistance with data collection.

REFRENCES

[1] Firk R., Stamer E., Junge W., et al. Automation of oestrus detection in dairy cows: a review. Livestock Production Science , 2002,75, 219-232.

[2] Cutullic E, Delaby L, Causeur D, et al. Hierarchy of factors affecting behavioural signs used for oestrus detection of Holstein and Normande dairy cows in a seasonal calving system[J]. Anim Reprod Sci. 2009, 113,22-37

[3] Brehme, U., Ahlers, D., Laufeld, P., et al. Brunsterkennung und Gesundheitsu¨berwachung mittels sensorgestu¨tzter Funkdatenlogger. In: Bau, Technik und Umwelt in der landwirtschaftlichen Nutztierhaltung, Beitra¨gezur5. Internationalen Tagung in Hohenheim Ma¨rz, 2001, 6-7, 44-49.

[4] Roger Müller, Lars Schrader. A new method to measure behavioural activity levels in dairy cows. Applied Animal Behaviour Science, 2003,83, 247-258.

[5] Guo Y., Poulton G., Corke P.,et al. Using accelerometer, high sample rate GPS and magnetometer data to develop a cattle movement and behaviour model. Ecological Modelling , 2009,220, 2068-2075.

[6] Steve Warren, Angel Martinez, Timothy Sobering. et al. Electrocardiographic Pill for Cattle Heart Rate Determination, 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August , 2008,20-24, 4852-4855.

[7] Van Eerdenburg Frank J. C. M. The pedometer, an automated aid in the detection of oestrous. Veterinary Quarterly , 2008,30(1), 49-57

[8] Jonsson R., Blanke M., Poulsen N. K. Oestrus detection in dairy cows from activity and lying data using on-line individual models. Computers and Electronics in Agriculture , 2010,76(1), 6-15.

[9] Nariyasu Watanabe, Seiichi Sakanoue, Kensuke Kawamura. et al. Development of an automatic classification system for eating, ruminating and resting behavior of cattle using an accelerometer. Japanese Society of Grassland Science, 2008,54, 231-237.

[10] Martiskainen Paula, Mikko Ja¨rvinen, Jukka-Pekka Sko¨n et al. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. Applied Animal Behaviour Science, 2009, 119, 32-38.

[11] Robert B., White B.J., Renter D.G. Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. Comput. Electron. Agric., 2009,67, 80-84.

[12] Yin Ling, Liu Caixing, Hong Tiansheng, et al. Design of system for monitoring dairy cattle's behavioral features based on wireless sensor networks. Chinese Society of Agricultural Engineering, 2010,26(3),203-208.

[13]]Holger Fr ¨ ohlich, Andreas Hoenselaar, Jonas Eichner et al. Automated classification of the behavior of rats in the forced swimming test with support vector machines, Neural Networks, 2010,21, 92-101.

[14] Cornou Ce´cile, Søren Lundbye-Christensen. Classifying sows' activity types from acceleration patterns An application of the Multi-Process Kalman Filter. Applied Animal Behaviour Science, 2008, 111,262-273.

[15] Cornou Cécile, Soren Lundbye-Christensen. Classification of sows' activity types from acceleration patterns using univariate and multivariate models. Comput. Electron. Agric. , 2010,72, 53-60.

[16] Juanying Xie, Shuai Jiang, Weixin Xie et al. An Efficient Global K-means Clustering Algorithm. Journal of Computers, 2011, 6 (2), 271-279

[17] Xiaohong Liu, Shujuan Yuan, Li Li. Prediction of Temperature Time Series Based on Wavelet Transform and Support Vector Machine. Journal of Computers,2012,7(9), 1911-1918

[18] Nielsen Lars Relund, Asger Roer Pedersen, Mette S. Herskin. et al. Quantifying walking and standing behaviour of dairy cows using a moving average based on output from an accelerometer. Applied Animal Behaviour Science 2010,127, 12-19.

[19] Yániz JL, Santolaria P, Giribet A et al. Factors affecting walking activity at estrus during postpartum period[J]. Theriogenology , 2010, 74,327-344

[20] Firk, R., Stamer, E., Junge,W., Krieter, J. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. Arch. Tierz., Dummerstorf. 2003,46(2),127-142

[21]]P. Løvendahl, M. G. G. Chagunda. On the use of physical activity monitoring for estrus detection in dairy cows. J. Dairy Sci. 2008,93,249-259

[22] J. Roelofs, F. López-Gatius,c, R.H.F. Hunter et al. When is a cow in estrus? Clinical and practical aspects. Theriogenology ,2010,74, 327-344

[23] Wilhelm Grzesiak, Daniel Zaborski, Piotr Sablik et al. Detection of cows with insemination problems using selected classification models. Computers and Electronics in Agriculture ,2010,74, 265-273

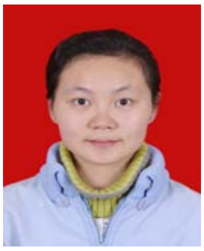
[24] Emanuel Garcia, Jan Hultgren, Pontus Fällman. Oestrous intensity is positively associated with reproductive outcome in high-producing dairy cows. Livestock Science 2011,139, 191-195

[25] A. Holman, J. Thompson, J. E. Routly et al. Comparison of oestrus detection methods in dairy cattle.Veterinary Record, 2011,169, 21-26

[26] F. Lo ´pez-Gatius, P. Santolaria, I. Mundet et al. Walking activity at estrus and subsequent fertility in dairy cows. Theriogenology ,2005,63,1419-1429

[27] Yu Zong, Ping Jin, Dongguan Xu, Rong Pan. A Clustering Algorithm based on Local Accumulative Knowledge. Journal of Computers, 2013, 8(2),365-371

[28] Jian Wu, Jie Xia, Jian-ming Chen, Zhi-ming Cui. Moving Object Classification Method Based on SOM and K-means. Journal of Computers, 2011, 6, (8), 1654-1661.



Ling Yin was born in Changsha, Hunan province of China in 1977. She received the doctor degree in agricultural electrification and automation from South China Agriculture University in 2011.

She worked in South China Agriculture University in 2003. Her present interests are wireless sensor network applications and agricultural data mining.

Tiansheng Hong was born in Meizhou, Guangdong province of China in 1955. He is a professor at South China Agriculture University, College of Engineering. His research interests are Agricultural Mechanical Engineering.

Caixing Liu was born in JieYang, Guangdong province of China in 1963. He is a professor at South China Agriculture University, College of Informatics. His research interests are wireless sensor network applications.