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ANALYSIS OF BIOLOGICAL DATA OF CATTLE AND WAVELET TRANSFORM BASED PREDICTION FOR OPTIMAL INSEMINATION PHASE

Takumi ASAOKA, Hiroto NOMA, Tatsuya KOMATSU, Hidetoshi OYA
Tokyo City University
0009-0002-5890-5470, 0009-0007-0972-8857, 0009-0008-1110-1217, 0000-0003-1046-5832
g2281401@tcu.ac.jp, g2381449@tcu.ac.jp g2281424@tcu.ac.jp, hide@tcu.ac.jp

Ryotaro MIURA
Nippon Veterinary and Life Science University
0000-0002-4945-0649
ryotaro.miura@gmail.com

Koji Yoshioka
Azabu University
0000-0003-1600-7955
k-yoshioka@azabu-u.ac.jp

ABSTRACT: For farmers who maintain dairy cattle, artificial insemination (AI) is one of important events in cattle, because it may lead to lose money by missing out on AI. However, the accuracy for detection depends on the time and number of observations when the estrus behavior and signs for cattle during the estrus season are visually assessed by experts and farmers, and the detection accuracy via experts and farmers is approximately 60%. For farmers, it is obvious that improving reproductive efficiency can save time and money. Therefore, various detection strategies for AI timing such as pedometers and methods based on observation of hormone in estrus have been well studied. Additionally, a detection strategy based on variations for temperature corresponding to ovulation has also been presented. In particular, the accuracy of detection of AI timing based on monitoring the vaginal temperature is greater than that for other methods such as pedometer and so on, i.e., it seems that an optimal timing of AI based on vaginal temperature in cattle is more effective. Although there are some existing results for detection of AI timing based on vaginal temperature and vaginal electrical resistance data, further improvement of accuracy is required in practical use. In this paper, we propose an estimation method for the optimal AI timing by analyzing both vaginal temperature and vaginal electrical resistance data. In our approach, as preprocessing, MaMeMi filter and Gaussian kernel smoother are newly introduced for the purpose of reducing the effect of circadian rhythms and various noises. Moreover, we adopt continuous wavelet transformation to analyze biological data, and NSI (Normalized Spectrum Index) is calculated. Finally, the optimal timing for AI can be estimated by using the Mahalanobis distance. In this paper, we present the proposed estimation algorithm and evaluate the proposed approach.

Key words: Artificial insemination (AI), Estimation of optimal AI timing, Continuous Wavelet Transform, NSI

INTRODUCTION

For farmers who raise dairy cattle, reproductive management is very important for production of successor cattle and ensuring a stable milk. Additionally, in the case of beef cattle, maintaining a stable conception rate is essential for planned successor calf production, and thus AI is a crucial event. However, when experts or farmers visually assess estrus, the accuracy of detection depends significantly on observation time and frequency, i.e. farmers suffer from a substantial labor burden. In fact, even with significant time spent on observation, the success rate of AI is only about 60% [Pennington, J. A. et al., 1986]. It is obvious that failing in AI leads to economic losses for farmers during the intervening period until the next estrus. Namely, it is the most important for improving reproductive efficiency, and it means that the optimal AI timing can be predicted accurately. Therefore, various studies have been tackled to maintain a stable conception rate. In the existing results [e.g. Higaki, S. et al., 2019, Onishi, Y. et al., 2014], the optimal timing for AI (ovulation period) is predicted by analyzing the vaginal temperature and electrical resistance for cattle. In the work of Onishi, Y. et al., 2014, a basic waveform synthesis approach based on Fourier series expansion is employed to capture the variations in biosignal data related to the timing of AI. However, further improvements are necessary in practical point of view for the accuracy of the optimal AI timing. In this study, based on the trends reported in literature [Higaki, S. et al., 2019], we analyze the vaginal temperature (VT) of cattle and introduce smoothing with Gaussian kernel as a preprocessing method. Moreover for preprocessing step for data analysis, we perform outlier correction after removing the influence of circadian rhythms. Furthermore, we introduce continuous wavelet transform, and scalogram can be obtained. Additionally, we calculate the Normalized Spectrum Index (NSI) and extract features parameters related to the ovulation period from NSI. Finally, by calculating the Mahalanobis distance from the obtained features, the

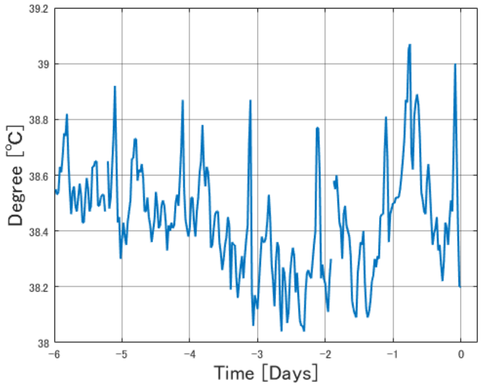

Figure 1:An example of vaginal temperature data.（No.62 1）

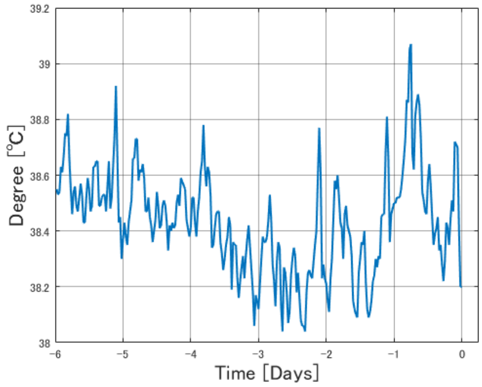

Figure 2:The waveform after outlier correction in Figure 1.

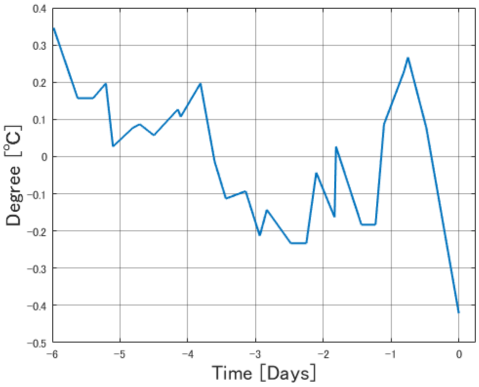

Figure 3:The waveform after bias removal in Figure 2.

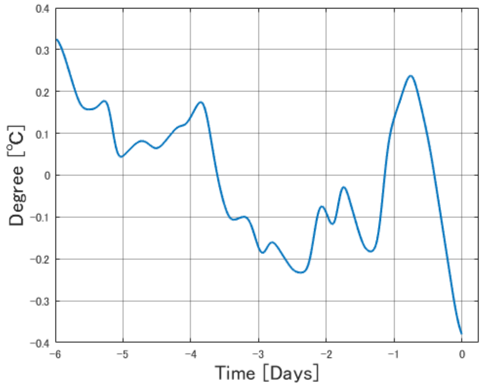

Figure 4:The waveform after smoothing in Figure 3.

optimal AI timing is predicted. In this paper, we show the proposed prediction system and its efficiency.

PREPROCESSING OF VAGINAL TEMPERATURE DATA

Correction of outliers

Measured biological data sometimes include some noises. These are unrelated to fluctuations of VT data due to ovulation, and may adversely affect the estimation of optimal AI timing. Therefore, as a first step, we perform a process to remove various noises, and suppress abrupt variations in data, i.e. outlier. In particular, if difference between adjacent points of VT data exceeds a prespecified threshold value occur, the data is considered abnormal and replaced with a larger value in the neighborhood. In this study, as in the previous study [Yoshioka, H. et al.,2015], the threshold was set to 3 times the median movement up to 1 day before in order to remove only abnormal variation without compromising temperature variation related to ovulation timing. Figure 2 shows the correction results of data shown in Figure 1.

Extraction of Minimum Values in Every 4 Hours and Bias Removal

In order to reduce the influence of circadian rhythms, we extract minimum values in every 4 hours from the data after outlier correction. To put into the concrete, the minimum value within a time interval of N [samples], and we consider this minimum value as the representative value within that interval. In this study, we select $N = 8$ [samples]. Next, bias removal can be done by subtracting the overall mean value from the data. Bias removal ensures that the data exhibits variations near 0[°C] on the vertical axis. Figure 3 represents the result for extraction of minimum values from the waveform in Figure 2.

Smoothing with Gaussian Kernel

After bias removal, smoothing is performed by using a Gaussian kernel. If we denote the input signal as $x(t)$ and the output signal as $y(t)$, then $y(t)$ is characterized by the variance σ^2, and the Gaussian function $g_{\sigma(t)}$ is given by

$$g_\sigma(t) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{\frac{t^2}{2\sigma^2}} \quad , \tag{1}$$

$$y(t) = \sum_{i=-n}^{n} g_\sigma(i)x(t+i) \quad . \tag{2}$$

In this study, the window width, which is denoted by n, is set at 14 [samples]. Figure 4 shows the result of smoothing result of the signal in Figure 3. It can be observed from Figures 3 and 4 that smoothing effectively plays.

MaMeMi Filter

In this study, the smoothed data is further processed with a type of low-pass filter called the MaMeMi filter. Here, for the input signal as $x(t)$ and the output of the MaMeMi filter as $h(t)$, then $h(t)$ is defined as follows:

$$h(t) \triangleq \frac{\max^\star(t) + \min^\star(t)}{2} \tag{3}$$

$$\max^\star(t) = \begin{cases} x(t) & (t = 0) \\ \max^*(t-1) + \sigma_m \times \delta & (x(t) > \max^\star(t-1)) \\ \max^*(t-1) + \delta & (x(t) \leq \max^\star(t-1)) \end{cases} \tag{4}$$

$$\min^\star(t) = \begin{cases} x(t) & (t = 0) \\ \min^*(t-1) - \sigma_m \times \delta & (x(t) > \min^\star(t-1)) \\ \min^*(t-1) + \delta\big(x(t) \geq \min^\star(t-1)\big) & \end{cases} \tag{5}$$

For the design parameters σ_m and δ in the MaMeMi filter, we tackled trial and error experiments so as to choose parameter settings that do not remove the characteristic of variations in VT data before ovulation. As a result of these experiments, these two parameters are selected as $\sigma_m = 9.0$ and $\delta = 0.001$, respectively. The result of applying the MaMeMi filter to the data in Figure 4 is shown in Figure 5.

ANALYSIS OF VAGINAL TEMPERATURE

Continuous Wavelet Transform

In literature [Yoshioka, H. et al.,2015], an approximation waveform of vaginal temperature and vaginal electrical resistance is generated using a fundamental waveform synthesis method based on Fourier series expansion. However, in this study, as in literatures [Onishi, Y. et al., 2014] and [Komatsu, T. et al., 2022], we adopt a continuous wavelet transform. Continuous wavelet transform is a technique that analyzes a given signal $\boldsymbol{f(t)}$ by translating and scaling a mother wavelet $\boldsymbol{\psi(t)}$. It is defined as follows:

$$\mathbf{W_{(\beta,\alpha)}} \triangleq \frac{\mathbf{1}}{\sqrt{\boldsymbol{\alpha}}} \int_{-\infty}^{\infty} \mathbf{f(t)} \overline{\boldsymbol{\psi}\left(\frac{\mathbf{t}-\boldsymbol{\beta}}{\boldsymbol{\alpha}}\right)} \mathbf{dt} \tag{6}$$

Here, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represent the scale parameter and shift parameter, respectively. It's worth noting that in this study, we adopted the Gabor mother wavelet defined as follows:

$$\psi(t) \triangleq \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{t^2}{2\sigma^2}} e^{j\omega_0 t} \tag{7}$$

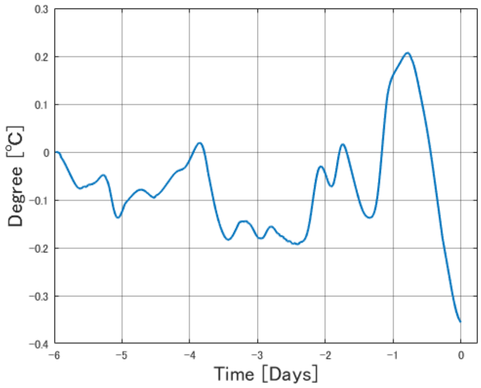

Figure 5:Waveforms after applying MaMeMi filter in Figure 4

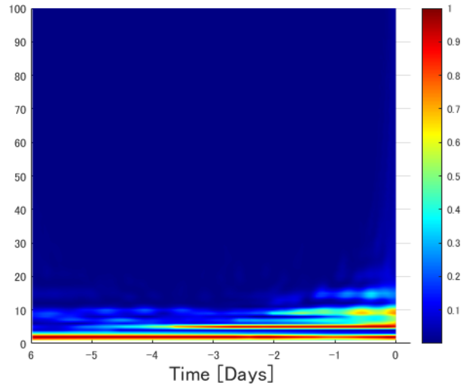

Figure 6:The scalogram of Figure 5.

where j is an imaginary unit, $\sigma_2 \in \mathbb{R}$ represents the variance of the normal distribution, and $\omega_0 \in \mathbb{R}$ denotes the base angular frequency. Note that Figure 6 is the spectrogram obtained from Figure 5. In the scalogram, the horizontal axis represents time [Days], the vertical one is frequency [Hz], and the color bar means the strength of energy of frequency elements. As evident from Figure 6, characteristic changes in the strength of energy [Power] just before ovulation can be observed. Thus, the use of the continuous wavelet transform is useful for estimation of AI timing.

NSI (Normalized Spectrum Index)

The scalogram shown in Figure 6 is three-dimensional data related to time-frequency-energy strength. Therefore, in order to capture the characteristics related to the ovulation timing, we adopt the Normalized Spectrum Index (NSI [Onishi, Y. et al., 2014]) and is calculated by

$$\mathrm{NSI}(k) = \frac{\sum_j \mathrm{E}_{(k,l)}\, \mathrm{f}_l}{\sum_l \mathrm{E}_{(k,l)}} \quad , \tag{8}$$

$$\mathrm{E}_{(k,l)} = \frac{\mathrm{W}(k,l)}{\max_l\left(\mathrm{W}(k,l)\right)} \quad . \tag{9}$$

NSI (Normalized Spectrum Index) represents the temporal transition of center of gravity in the spectrogram. In equation (8), k is the sample number on the time axis, l is the sample number on the frequency axis, and f_l means the frequency of the l sample. Here, Figure 7 represent the NSI which is obtained from the scalogram in Figure 6. One can see from Figure 7 that peaks in NSI around -1~0 [Days], and the characteristic changes corresponding to ovulation can be captured.

CONSTRUCTION AND VALIDATION OF THE AI TIMING PREDICTION SYSTEM

In the proposed method, we extract features from the distinctive variations around -1~0 [Days] in NSI and use these features. For prediction of the optimal AI timing, Mahalanobis distance is utilized. The extracted features include 'Change in the past 6 hours,' 'Difference from the median of the past 6 hours,' and 'Difference from the median of the past 12 hours,' as mentioned in literature [Komatsu, T. et al., 2022]. These three features are extracted from NSI. As shown in Figure 8 (see the top of the next page), the Mahalanobis distance takes its minimum value around -1~0 [Days]. This indicates that the method effectively captures the characteristics just before ovulation. In this study, in order to identify the ovulation period, we set a threshold for the Mahalanobis distance at 0.0005, and the time when the threshold is exceeded as -12 [Hours] is extracted. Next, we verify the performance of the proposed prediction system of AI timing. Table 1 shows the estimation results obtained by using the proposed system. 'Diff[Hour]' is the difference between the estimated time and -12 [Hours]. From Table 1, we can observe that the estimation error for 12 hours before ovulation ranges from -7 to -2 hours. According to literatures [Koyama, K. et al., 2023, Sumiyoshi, T. et al., 2020], the optimal timing for AI is 6-18 hours before ovulation, and the effective period is 0-24 hours before ovulation. When the proposed method detects the time as

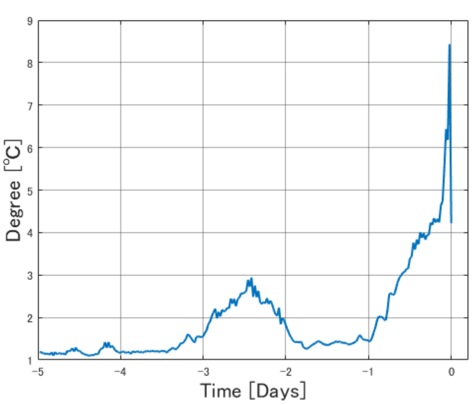

Figure 7:The NSI obtained from Figure 6.

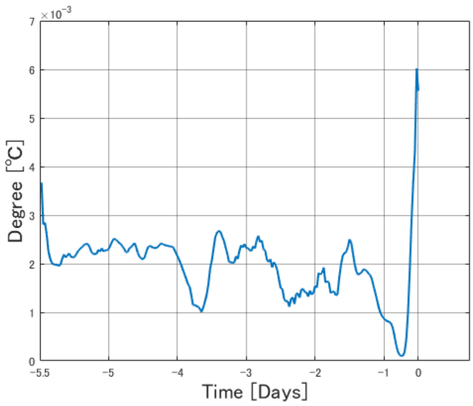

Figure 8:The Mahalanobis distance

Table 1. Estimation results for AI timing

No.	62_1	62_2	63	64_3	69	70	70_2	71
Diff[hour]	-7.0	-7.0	-2.0	-3.0	-6.5	-3.5		-2.5

12 hours before ovulation, we select AI timing as the time approximately 12 hours later. As a result, 7 out of 8 data are included in the optimal AI timing.

CONCLUSION

In this paper, we have proposed a prediction system based on analysis results of the biological data (vaginal temperature:VT) for cattle. To develop the proposed prediction system, preprocessing steps such as 4-hourly minimum value extraction, MaMeMi filter and so on are firstly executed. Next, by using continuous wavelet transform, VT data is analyzed, and the Normalized Spectrum Index (NSI) from the scalogram is calculated. From the NSI, feature parameters related to ovulation is derived, and by calculating the Mahalanobis distance based on these feature parameters the proposed system detects the time corresponding to AI timing. In the proposed system, 12 hours later the detected time is AI timing. Additionally, the estimation accuracy of the proposed system has been shown.

Future research subjects include increasing the amount of data to enhance the system's accuracy, exploring features contributing to the prediction of the AI timing, and discussion of preprocessing methods.

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