Dynamic time warping for classifying lameness in cows

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Abstract: Lameness in dairy cows is one of the most significant welfare and productivity issue. This work is mainly concerned with an automated detecting system for classifying lameness in dairy cows. In the proposed system, Dynamic Time Warping (DTW) is used to measure the similarity between two-time series. The first time series is the behavioral time periods of the cow used as the templates, which was collected while the cow was sound. The second time series is the behavioral time periods of the cow on each day used for testing. This process results in accumulated distance that is compared with a threshold value for classifying lameness. In the case of studies, three cows were used in experiments. The classified results show that the proposed algorithm can correctly classify lame and non-lame cows.

Keywords: lameness, behavioral time periods of cows, dynamic time warping.

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1 Introduction

Lameness in dairy cows is highly prevalent and painful. These impacts potentially affect not only animal welfare (Klaas et al., 2003) but also farm economies (Enting et al., 1997). Lameness causes losses in milk production and leads to an early culling of animals (Green et al., 2002).

Nowadays, the most common methods used for lameness detection and assessment are various visual locomotion scoring systems (Winckler and Willen, 2001; Flower and Weary, 2006). However, such method requires experience to be conducted properly, this is very labor intensive as an on-farm method, and the results are subjective (Winckler and Willen, 2001).

In literature, several authors have addressed the problems of lameness by developing the automated system.

The first automated system used a force plate to measure the ground reaction forces when cows walking (Rajkondawar et al., 2002) and was developed to measure weight distribution while standing (Neveux et al., 2006; Pastell et al., 2006; Rushen et al., 2007; Pastell and Madsen, 2008). Due to lameness reflects pain while walking, weight distribution during the cow standing might not always reflect the lameness while walking (Leach et al., 2010).

In further studies, Flower et al. (2005) were the first to use vision techniques with body markers to measure temporal and spatial gait characteristics in cows related to lameness. Song et al. (2008) used video images of walking cows without body markers to automatically measure step overlap as a relevant gait characteristic for lameness detection. There has been related studies using computer vision to analyze gait feature and posture variables that are back arch curvature (Poursaberi et al., 2010; Viazzi et al, 2014), step overlap (Pluk et al., 2010), hoof release angles (Pluk et al., 2012), the body movement pattern (Poursaberi et al., 2011) and was developed by a three-dimensional (3D) camera (Van hertem, et al., 2014). However, such systems are limited to measure a single or few steps and need fixed location to perform measurements, which are difficult in practice. Moreover, the accuracy of the methods could be

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improved in the case of measurement of the gait features from several consecutive steps from a walking cow.

In a different way, accelerometers were used to measure the activity or gait features of cows and their relation to lameness. Pastell et al. (2009) used a custom-made wireless 3D accelerometer system to measure temporal gait characteristics on all 4 limbs of the cows. Differences in symmetry variance and forward acceleration were observed between lame and non-lame cows. Although this technique does not need to fix location, it requires four embedded systems to measure the gait characteristics. Alsaaod et al. (2012) used accelerometer attached to one of the front legs of the cows to measure activity and lying behavior. They were able to predict lameness in cows with an accuracy of 76% based on deviations from normal behavior. However, this technique needs many parameters in a process such as step impulses, lying time, numbers of bouts, the median of the duration for one bout period, the minimal and maximal duration of one bout.

From the literature above, the aim of this work is intended to diagnose the lameness of cows. The behavioral time periods of the cow in each day are measured the similarity with those of the cow collected while the cow was sound by using DTW. The results of this process can predict that cow is lame or non-lame.

This paper is organized as follows: Section II gives the material for measuring the behavioral time periods of a cow and the method for classifying lameness in cows. Section III shows the experimental results for the classification success rate. Finally, Section IV concludes the studied results of the proposed system.

2 Material and method

2.1 Measuring the behavioral time periods of a cow

In this subsection, we explain the method for measuring the behavioral time periods of a cow based on a simple classification technique (Apinan et al. 2015). The embedded system was fitted around a leg of the cow as shown in Figure 1. For the relationship between the acceleration and the angle of each axis, when the cow is standing, the Y and Z-axis are perpendicular to a leg while the X-axis is perpendicular to the ground.

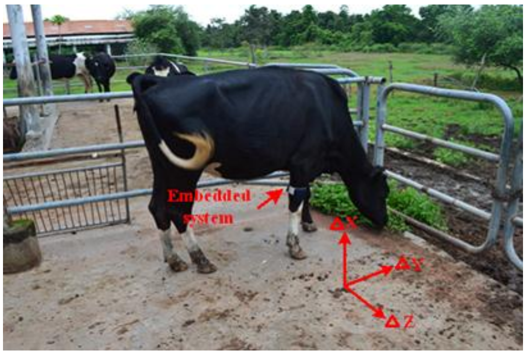

Figure 1 Embedded system attached around a leg of the cow.

Considering the flowchart in Figure 2, every 60 data (60 seconds) the average of each axis is found as $\overline{C_X}$, $\overline{C_Y}$, and $\overline{C_Z}$ and then is compared with references of each axis $\bar{R}_{rX}$, $\bar{R}_{rY}$, and $\bar{R}_{rZ}$, respectively. Thus, the results of decision tree process, the cow behaviors are classified into two groups: 1) standing and walking-grazing behaviors and 2) lying behavior. While the behavioral classification in group 1, the acceleration signals of standing behavior are similar to those of walking-grazing behavior. Therefore, it is difficult to use the average of the accelerometer signals in classification. However, the variance of the acceleration signal of Y-axis, σ_Y^2, while the cow is walking-grazing is higher than while standing. Thus, the variance of the Y-axis is used for classifying the both behaviors.

2.2 Classification of lameness in cows

2.2.1 Signal preprocessing for DTW

After the accelerometer data were classified into behaviors in the form of time as shown black boxes of the flowchart in Figure 2.

Let us consider the red boxes in Figure 2, we start at the behavioral time periods of the cow that are converted by using conditions as follows:

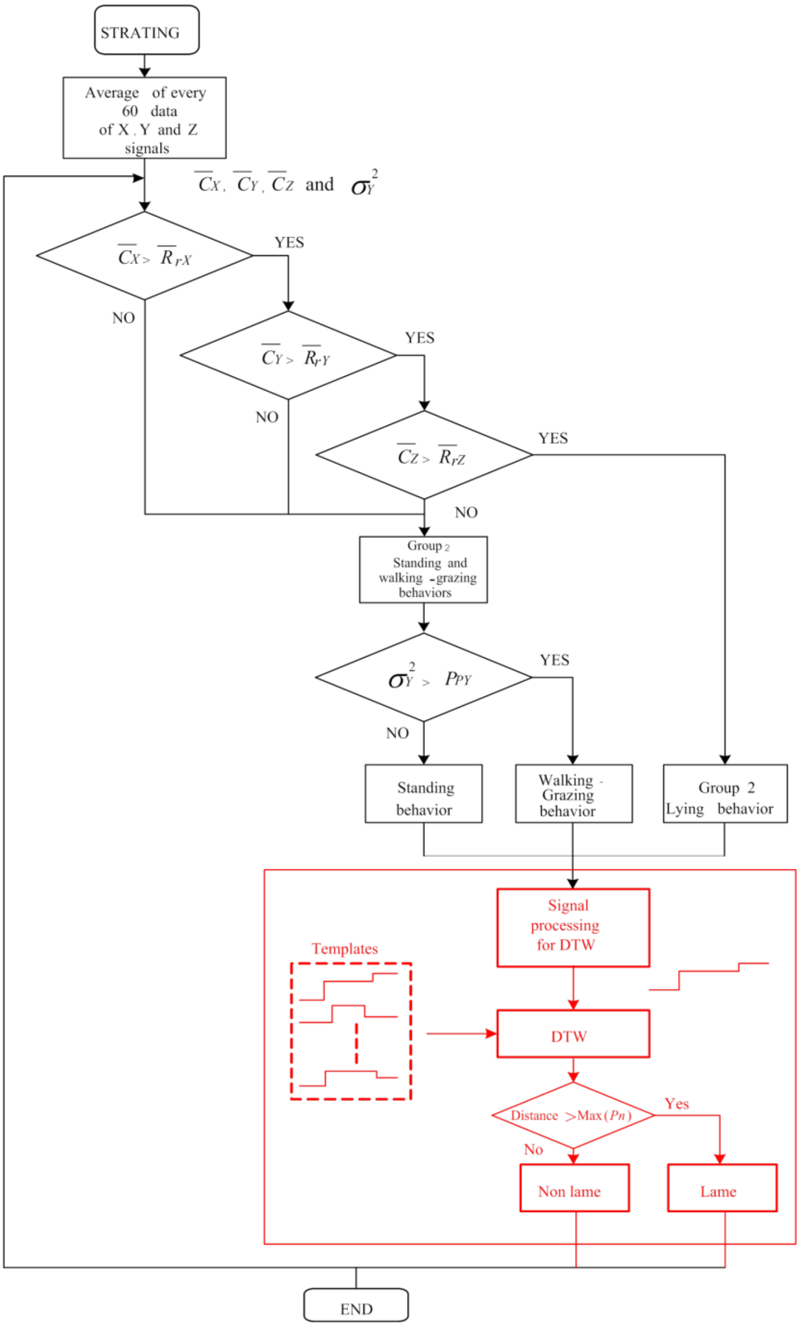

Figure 2 Lameness classification flowcharts in dairy cow.

2.3 Classification of lameness in cows

2.3.1 Signal preprocessing for DTW

$$\text{Lying time} = 1.5 \text{ V}$$
$$\text{Standing time} = 2.5 \text{ V}$$
$$\text{Walking} - \text{grazing} = 3.0 \text{ V} \qquad (1)$$

Figure 3 shows the transform of the behavioral time periods of the cow. The vertical and horizontal axes are the voltage level and time, respectively.

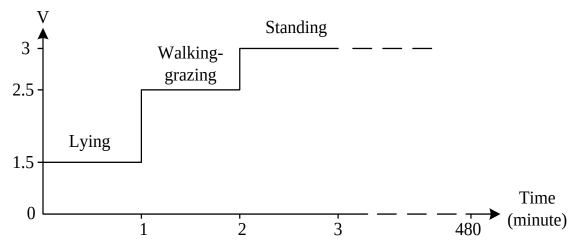

Figure 3 Behavioral time periods of the cow.

2.2.2 Dynamic time warping

Dynamic time warping is an algorithm for measuring the similarity between two-time series, which may vary in time or speed. The essence of DTW is to find the path through the observations that would lead to the minimum global cost by minimizing the local cost. By continually minimizing the local cost through using dynamic programming, a global minimal error measurement is achieved. In mathematical terms, the global cost matrix D between two-time series is created by the Equation:

$$D(i,j) = d(i,j) + min_{p(i,j)}\{D[p(i,j)] + T[(i,j),p(i,j)]\} \quad (2)$$

Where $d(i,j)$ is the local cost between frame i of the first series and frame j of the second series, $p(i,j)$ is the set of possible previous costs to i,j and $T$is the cost function (Giorgino. 2009). Each element in matrix D contains the minimum error between frames i and j based on adding the local cost $d(i,j)$ to the minimum error of frames $(i-1,j)$, $(i,j-1)$ and $(i-1,j-1)$. Hence, the bottom-right value of the matrix D would yield the minimum global error between the two-time series and that is reached by minimizing the local errors between the two-time series. Figure 4 shows the accumulated cost matrix and optimal warping path of DTW where the vertical axis is the template or the behavioral time periods of the cow collected while the cow was sound and the horizontal axis is the behavioral time periods of the cow for testing. For the data number, we set the behavioral time periods of the cow at 480 minutes ($n = m = 480$).

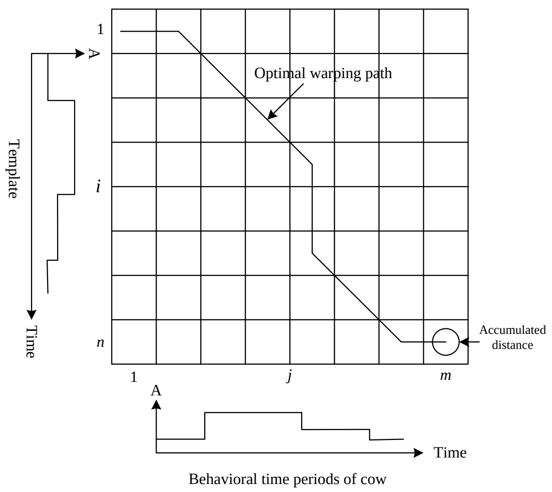

Figure 4 Accumulated cost matrix and optimal warping path.

2.2.3 Threshold for classifying lameness

The templates of behavioral time periods of the cow were measured while the cow was sound. One template can be used for processing in classification. However, in each day, the sound cow may little change the behavioral time periods. This may cause errors in classified processing. Therefore, to improve an accuracy of classification rate, N templates should be used. Each template is measured similarity to another template. This process results the set of accumulated distances, P_n where n is 1, 2…$\frac{N!}{2(N-2)!}$.

The value of accumulated distances in the set of P_n should be low because it indicates similarity of all templates. Thus, the maximum value of accumulated distances in the set of P_n could be used as a threshold for classifying lameness.

2.2.4 Templates versus behavioral time periods for testing

The behavioral time periods of the cow in each day or signal for testing are measured similarity to each template. If there is an accumulated distance lower than the threshold, it means that the signal for testing is similar to a template. The result is that the cow is normal. On the other hand, if all results of accumulated distance are higher than the threshold, it means that the signal for testing is different from the templates. The result of the system will be shown that the cow is developing in lameness.

3 Experimental results

The experiments were tested at the Mahasarakarm University in Thailand with three cows. The cows were released from the corral for looking for grass in the field during 8.00 AM - 4.00 PM. In the first step, the reference voltage averages of each axis for classifying the standing and walking-grazing activities from the lying activity were found as $\bar{R}_{rX} = 1.82$, $\bar{R}_{rY} = 1.52$, and $\bar{R}_{rZ} = 1.57$. While the reference variance value of the Y-axis for classifying the standing and the walking-grazing activities was found at $P_{PY} = 0.0031$.

In the second step, we examine the experiments of the proposed algorithm for classifying lameness by three cases as follows:

1) The first case with the cow#1, the behavioral time periods of the cow while cow#1 was sound recorded to be templates. Figure 5 shows the examples of the behavioral time periods on the first and second day. These signals were measured similarity by using DTW. The result of this process shows that the accumulated distance is equal to 1.25 as shown in Figure 6. While on the third-tenth day, the cow was still sound. The behavioral time periods of the cow during these days shows little changed. Therefore, the DTW process results in the maximum of accumulated distance as 1.45. This value can be used as the threshold for classifying its lameness.

2) The second case with cow#2, the behavioral time periods during the first and second day is shown in Figure 7. While Figure 8 shows accumulated cost matrix and optimal warping path. In this case, we know that the cow was developing lameness during the first-fourth day. We used DTW for measuring the similarity of the behavioral time periods on these days. We found that the maximum of accumulated distance is 36.75. This value is high because of the difference of signals.

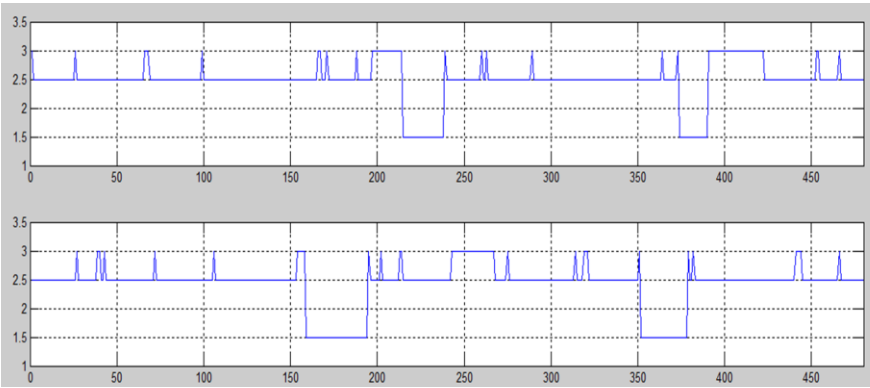

Figure 5 Behavioral time periods of cow#1 on the first and second day.

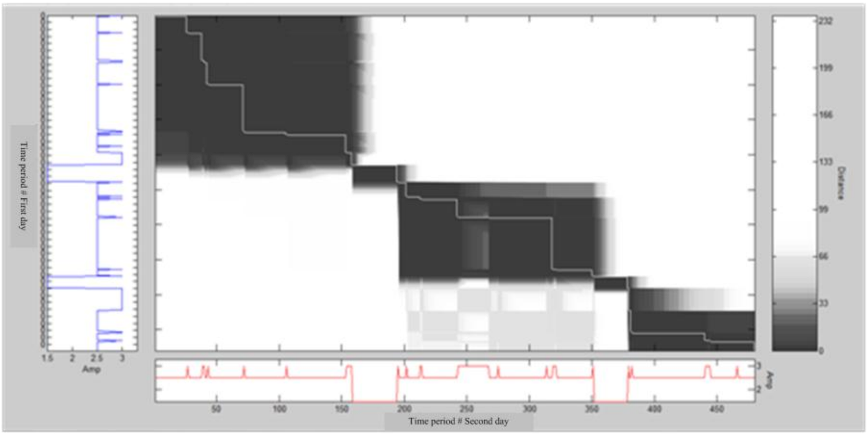

Figure 6 Accumulated cost matrix and optimal warping path of cow#1 on the first and the second day.

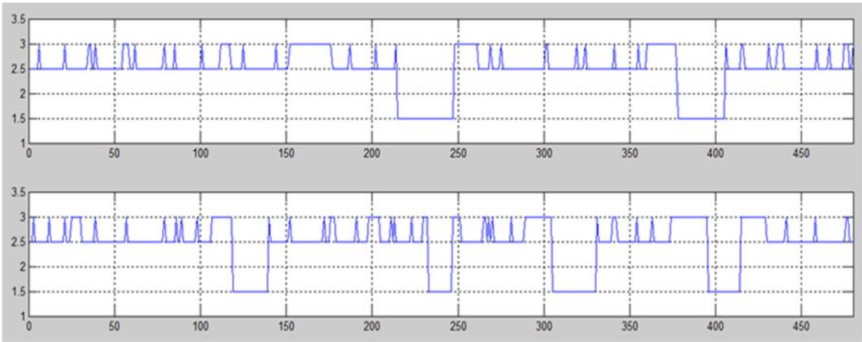

Figure 7 Behavioral time periods of cow#2 on the first and second day.

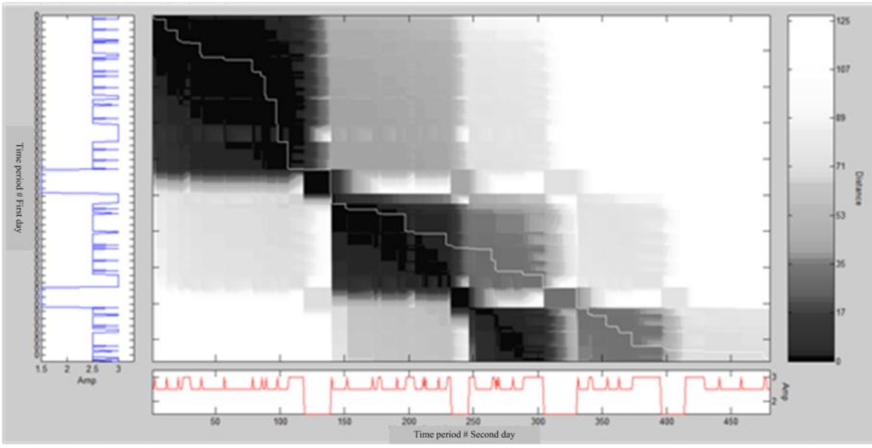

Figure 8 Accumulated cost matrix and optimal warping path of cow#2 on the first and the second day.

Figure 9 Behavioral time periods of cow#3 during on estrus period.

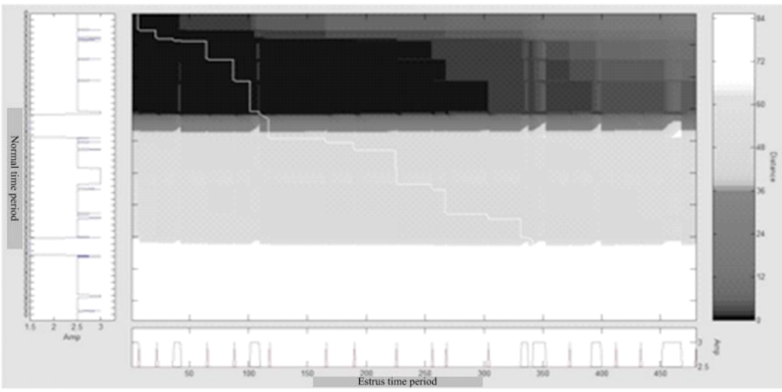

Figure 10 Accumulated cost matrix and optimal warping path of cow#3 during on normal and estrus periods.

On the fifth day, the cow became normal. We used DTW measuring the similarity between the behavioral time periods on the fifth day with those on the first-fourth day. The results of these processes, the accumulated distances are 4.75, 30.35, 20.75 and 5.55 respectively. While the maximum value of accumulated distances of the behavioral time periods during the fifth-tenth day is

1.55. This result shows that it could be used as the threshold for classifying lameness.

3) In the third case with cow#3, we recorded the behavioral time periods for 5 days before the cow is in estrus period. The behavioral time periods of these days were processed by the proposed algorithm resulting in the maximum value of accumulated distances as 1.45. This value is used as the threshold for classifying lameness. Furthermore, it can be used as the threshold for classifying estrus. Figure 9 shows the behavioral time periods of the cow during estrus period. Note that when a cow is an estrus, not lying. Figure 10 shows the accumulated cost matrix and optimal warping path during the cow is normal and in estrus period.

The accumulated distance is much higher than 1.45.

4 Conclusions

This paper presented the technique for classifying lameness by using behavioral time periods of a cow. In the proposed technique, the behavioral time periods of the cow used as the templates which were recorded while the cow was sound. These templates are used to measure similarity with the behavioral time periods of the cow on each day by using Dynamic Time Warping. The maximum of accumulated distances, the threshold value for classifying lameness, is found by measuring the similarity of all templates. The results of classification show that the proposed algorithm can correctly classify lameness in cows. Furthermore, it can be still used for classifying cow in estrus period.

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