Markov Chain Techniques for Cow Behavior Analysis in Video-based Monitoring System

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Abstract—**In this paper we shall explore and examine how Markov Chain techniques of stochastic processes can be utilized to analyze cow behaviors in video-based monitoring systems. In this aspect due to shortage of human experts for monitoring the video-based monitoring system has become a powerful technique to replace for human experts. Moreover the image processing methods will play major roles in analyzing visual behaviors such as cow identification, estrus detection, prediction of calving time and body condition scoring etc. Since cow behaviors are changing with respect to times and related to immediate past, Markov Chain models will be very useful enforce the image processing techniques. Although there has been a tremendous amount of methods for detecting estrus, still it needs to improve for achieving a more accurate and practical. Thus in this paper, cow behaviors are to be analyzed by using Gamma Type Markov Chain Models. In particular, image processing methods will be performed to detect cow activities such as standing, lying and walking in association with time, space and frequencies. Then collected data are to be modeled by using Markov Chain for decision making process. As an illustration, we provide some simulation results based on gamma random number generated data.**

Index Terms—**body condition score, cow behaviors, estrus detection, Markov Chain, video-based monitoring**

I. Introduction

In precision dairy farming, more and more attentions are given on the video-based cow behavior monitoring systems for automated detecting normal or abnormal (unhealthy) actions so that the necessary remedies should be taken in right time. Especially, it is very beneficial to the large scale farms, if an efficient automated heat detection system could be established to accurately determine when the cows are ready for insemination. Accurate detection of heat detection, correct body condition scoring system and correct prediction of calving time are essential for the precision dairy farms.

Many researchers [1]-[5] have studied and proposed various methods for the developments of monitoring systems. But still it is needed to improve to achieve high accuracy rates. On the other hand the dairy farmers are eager to optimize lactation and to minimize the dry-off periods that requires to accurately identify when the cow is in heat [6].

The costs of poor performance in the aspect of the farming operation are high because of later calving, lost milk production and fewer artificially bred replacement heifers. Recent reports have estimated the annual costs to the industry at around $65 million for missed heats alone with additional costs incurred as a result of inseminating cows when they are not in estrus. In addition, the quantity and quality of labor required for successful heat detection is an important factor to productivity gains, especially on larger farms. Such cattle monitoring system could support cattle reproduction by improving estrus detection. This will lead to a successful in breeding as well as an increase in milk production.

Therefore, in this paper vided-based monitoring system for cow behavior analysis is proposed by using Markov Chain models. In order to realize the proposed system, the rest of the paper is organized as follows. In section 2, some related works are described followed by the overview of the system architecture is described in section 3. Then some illustrative simulation results are presented in section 4. Finally, we conclude the paper in section 5.

II. Some Related Works

Over the past few years a tremendous amount of researches [2], [7], [8] have been done by various researchers concerning with cow behavior analysis. However we do not have much satisfactory results yet. Still there are many research areas needed to be thoroughly investigated. For example, there exist several challenging problems concerning with estrous detection on farms. One is the reduction of the duration of estrus behavior due to increased milk production near the time of estrus causing to the shorter time duration for detecting estrus visually. In some cases, the number of cows expressing standing estrus becomes smaller, silent ovulations are difficult to detect and expression of estrous behavior due to confinement are also reduced. Unless we can make an efficiency of estrous detection it would increase a big gap between after calving time and next to first Artificial Insemination (AI) time. On the other hand, it will also increase the average interval between AI services thereby limiting the rate at which cows become pregnant.

Thus it is clear that the impact of AI service rate on reproductive performance and visual heat detection problems are needed to be focused. This fact has been led to develop new electronic systems that incorporate activity monitoring as a means to associate increased physical activity with estrous behavior in cattle. In these research areas, a tremendous amount of literature exists for measuring the accuracy and efficacy of using various technologies to predict ovulation

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and timing of AI in relation to ovulation in lactating dairy cows. But only a few studies have investigated intelligent activity monitors for such purposes. For example how to determine the optimal reproductive times by monitoring as well as individual calf delivery to avoid the loss of calves to death or disease. The feeding pattern for each individual cow can also be monitored to fit their specific dietary needs to ensure maximum milk yields and healthy conditions.

In addition, by analyzing the detected motion data and the uncommon behavior data, one can diagnose some unhealthy forms of patterns such as lameness [3], [9]. It is also worthwhile to note that increased milk productivity can be ensured when the cow is lactating at peak production rates for the maximum amount of time. For this purpose, milk producers must identify and exploit key phases of the bovine reproductive cycle [10], [11]. In order to minimize the dry period we need to detect the cow is in heat accurately [12] so that the dairy farmers can have the optimal timing for Artificial Insemination (AI). This method is very appealing for reproduction and at the same time it can prevent the spread of genetic disease and enable to produce offspring with high-yield milk production [13], [14]. In order to perform AI successfully, it is natural and sounds logical to have timely and accurate information to determine if the cow is in heat. Some examples of cow activities are shown in Figure 1.

III. Overview of Proposed Method

The general overview of Markov Chain model for video-based cow monitoring system is described in Figure 2. It is composed of four components, visual monitoring component, image processing component, Markov Chain component and output display component. Depending on the size of monitoring areas, the number of visual cameras will be set up in the first component. By using the video sequences collected from the first component will be processed by using image processing techniques in component 2. Specifically the second component will produce various activities such as lying, standing and walking and etc.

Then those output data are to be used in the Markov Chain model of third component. In particular we employ Gamma based Markov Chain model to investigate the cow behaviors. Then, the model parameter estimation procedure module systematically learns the set of parameters involved in the behavior model (e.g. linear regression on feature points) making use of the labeled dataset. An illustration of Gamma probability density function is shown in Figure 3.

Finally the last component makes decision process for producing correct behavior of cow situation.

(a) (b)

Fig. 1 Some Examples of Cow Activities: (a) No Interaction Behavior within Cow Group, (b) Standing Cow

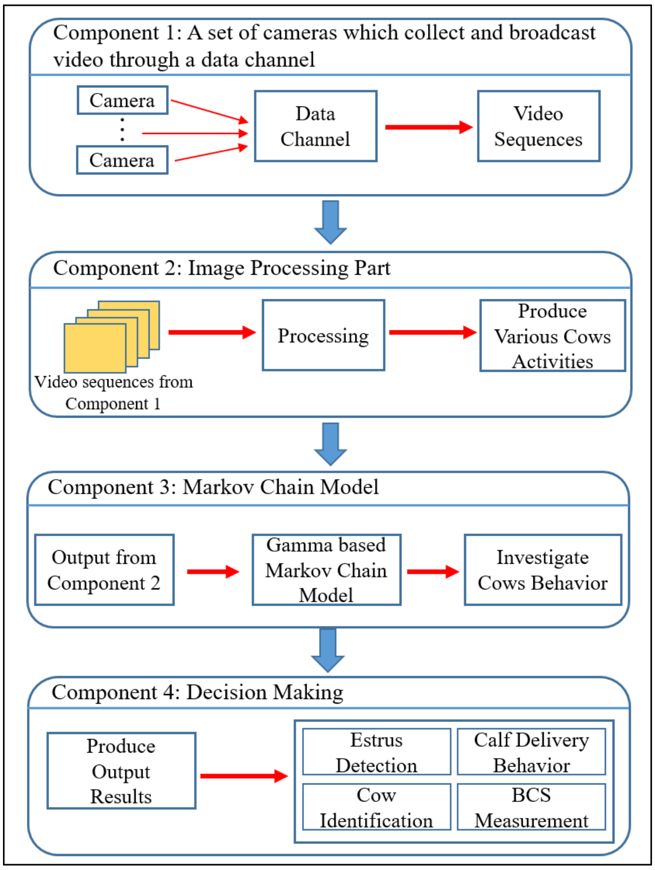

Fig. 2. Overview of Proposed Framework

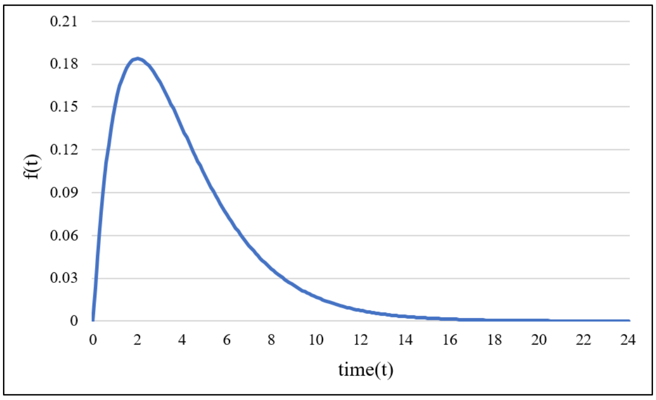

Fig. 3. An Illustration of Gamma Probability Density Function Graph

IV. Some Illustrative Simulation Results

In this section, we shall present some illustrative simulation results for the proposed dairy cow monitoring framework model.

It has been long recognized that many different types of prediction curves such as lactation curve pattern, optimal time of artificial insemination and estrus behavior patterns and body condition scores changing patterns and calving behaviors. These curves provide key information needed for dairy farmers. For example lactation curve tells us about milk yield patterns, when will be the optimal time for a cow showing the high estrus behavior pattern at which the artificial insemination should be made is very important for a dairy farm too. In similar fashion, the changes of body condition scores and calving behavior are key information for establishing a modern precision dairy farm. Sometimes it may

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not be easy to get test time data due to unexpected situations. In such cases our illustrative simulation models would be beneficial and could be used dairy management tools. In order to do so, we shall use three types of Gamma Markov Models for illustration.

A. Illustrative Simulation Model for Body Condition Scores (BCS)

The 1 to 5 point scales for BCS will be used with 0.25 increments where 1 represents thin cows and 4.5 above represent fat cows. According to this scale system, the possible number of scores can vary 1 to 17 different scores.

In this simulation, we assume the pattern of BCS curves follow a generalized gamma probability distribution described in equation (1);

$$B(t,a,b,c) = c\frac{t^{bc-1}}{\Gamma(b)}e^{-t^c} \qquad (1)$$

A particular type of gamma distribution has been used for lactation curve fitting by several researchers for example see in [15], [16]. In this model, $B(t, a, b, c)$ represents the weekly BCS on week t and parameter a is an average weekly score for particular lactation, b stands for increment and c stands for decrement rate. These parameters are estimated by using generated gamma based random numbers. Specifically, the scale parameter a taken as 1 in all the simulations since this parameter just affects to the scale of the data. Both, the c parameter and the b parameter are obtained from random samples of a uniform distribution in the interval [0-1].

The simulation results are shown in Figure 4 and Figure 5. It can be seen that the body scoring drops below 4 but it increases until dry periods. Again due to activation the BCS score a little drops down and up again until next calving. But we must be careful if the BCS increases over 4.5 in such case some health condition of cow should be checked.

B. Simulation Results for Estrus Detection

We shall now illustrate some simulation model of our proposed framework for estrus detection. In this model we will use the relationship between high activity such as interaction of multiple cows or single cow and low activity such as lying with rumination and chewing. We consider 8 activities of a cow during estrus cycles. They are:

A1: Lying Down with Bite and Rumination Chewing (LB)
A2: Lying Down without Bite and Rumination Chewing (LNB)
A3: Standing up with Bite and Rumination Chewing (SB)
A4: Standing up without Bite and Rumination Chewing (SNB)
A5: Walking with Bite and Rumination Chewing (WB)
A6: Walking without Bite and Rumination Chewing (WNB)
A7: Single Interactions (SI)
A8: Multiple Interactions (MI)

For each activity we divide into three levels high, medium and low performance. In order to create a synthetic dataset, we collect Gamma probability based random number generation by varying shape and scale parameters.

We then have an 8 by 3 matrix

(say) $C = [c_{ij}]$,

where,

c_{ij} = a random number generated from the gamma probability density function.

From this matrix C, we deduced two matrices of 8×8 and 3×3 to form Markov transition matrices such as,

$A = CC^T$ (i.e. 8×8) and

$B = C^TC$ (i.e. 3×3) after normalization.

In usual ways, we calculate the stationary distributions of the Markov Chains.

As an example we have the following two stationary distributions $\pi(A)$ and $\pi(B)$ of A and B respectively for shape parameter 1 and scale parameter 1.

$\pi(A)$ = [0.125521 0.125708 0.125332 0.125548 0.124389 0.124767 0.123914 0.124821]

$\pi(B)$ = [0.662177 0.200041 0.137783]

By varying the parameters of shape and scales we have the following graphs for three levels of high, medium and low respectively.

From both Figure 6 and Figure 7 show that the difference between the high and low activities is big at the time of day 1 and day 20 at which the decision can be made the cow is in heat and it is the optimal time for insemination. So we can continue the process when the next heat may arise.

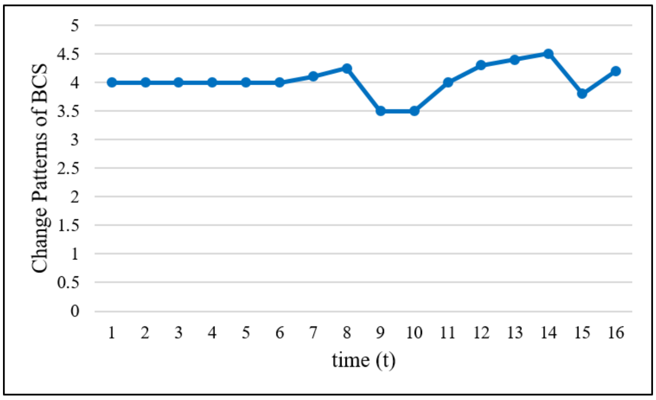

Fig. 4. Conceptual Graph for Body Condition Scores

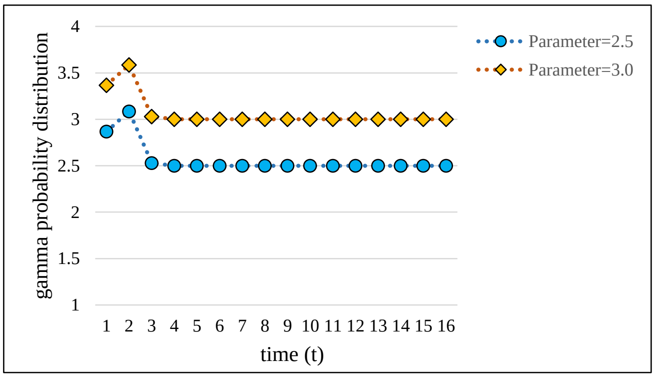

Fig. 5. Graph of Body Condition Scores with Variable Parameter

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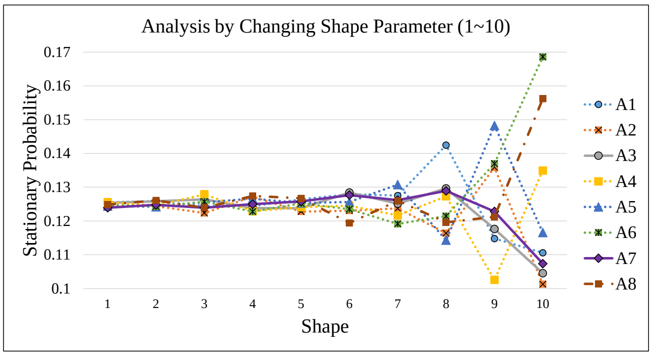

Fig. 6. Activity Graph for 8 Actions

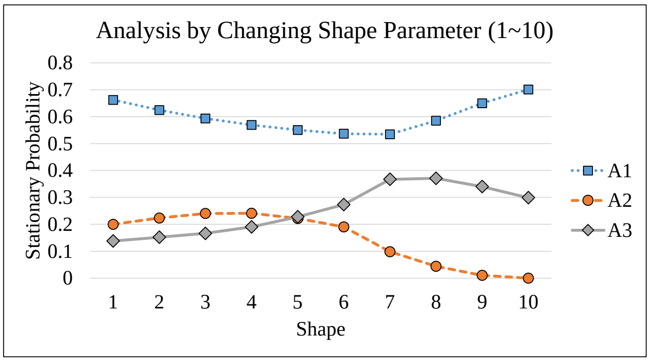

Fig. 7. Activity Graph for 3 Levels

V. CONCLUSIONS

In this paper we have outlined a monitoring framework for dairy cows for further investigation of various analysis such estrus or heat detection to find an optimal time at which an artificial insemination could be done. Moreover, how the body condition scores pattern is changed with respect time, body weight and milk yields and so on. This proposed framework is only its infancy state, more works to be done theoretically as well as experimentally. We shall be doing on this research to make more and more attractable and applicable leading to modern precision dairy farming.

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