Development of an Automated Cows In-Heat Detection and Monitoring System Using Image Recognition with GSM Based Notification System

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***Abstract*—Precise estrus detection is a factor for the reproductive performance of cows. The primary sign of estrus is the standing heat wherein a cow stands still for a few seconds while mating with other cows. Visual monitoring is the most common method used for detection of estrus that requires farmers' time and attention for high yield. In this study, an estrus detection using image recognition is used to detect the standing heat. The system is comprised of detection, identification, and notification system. Scale Invariant Feature Transform (SIFT) is responsible for the detection and identification of in-heat cows. Using SIFT, the images of cows were registered in the database, these images were used for detection and identification of cows and an algorithm for feature overlapping were created to detect the standing heat. When a standing heat is detected, it is recorded into the computer and simultaneously the Global System for Mobile Communications (GSM) module will send an alert message.**

***Keywords:* estrus, in-heat cows, standing heat, image recognition, artificial insemination**

I. Introduction

The Philippine cattle industry is one of the least developed commodities in the past years [1]. The high slaughter rate causes the declining population of the cattle. The average growth rate of cattle population in the Asian region is at 2.7%. In Indo-China and Cambodia, specifically, the growth rate is 8.6 %. Meanwhile, Laos, and Vietnam both have a 7.5 % growth rate. This is followed by Indonesia with a growth rate of 3.5% and then, Myanmar at 0.4%. The Philippines, however has a negative growth rate. The slaughter rate of the cattle was 4.88 % which is relatively higher than the previous years [1]. In 2010, the government imported cattle for breeding, which caused an increase in the growth of the population of the cattle from 2010 to 2015 [2]. The efficiency and determination the optimum time for insemination of cattle is beneficial to increase the pregnancy rate and consequently lead to economic growth resulting to less importation of cattle. The failure to detect estrus (heat) is considered as one of the major factors for low fertility of cattle [3]. Hence, for the dairy farmers, it is important to detect estrus in cattle.

Due to the insufficient detection of estrus, the reproduction growth in cattle decreases which subsequently leads to the increase cost due to the artificial insemination. A cow in heat usually stands still to be mounted 20 to 55 times and each mount lasts 3 to 7 seconds. In using artificial insemination, the optimal time is 8 to 12 hours after the first standing heat. Therefore, an effective estrus detection is very important to predict their heat condition [3]. The average number of standing events ranges between 6 to 9 per estrus to be consider in heat [4]. There are new technologies developed to detect estrus better than visual observation. There are past studies that have shown a concrete result of the efficiency and effectiveness of estrus detection. Using only visual monitoring is time-consuming and requires repetitive actions that need to be done frequently [5].

Using an estrus detection for monitoring is not new for the dairy farmers, but the dairy producers is interested to a modern, low cost, user-friendly and advance monitoring systems, hence this study. The main objective of this study is to develop an estrus detection system for Philippine cows.

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II. TECHNOLOGIES FOR ESTRUS DETECTION

A. Related Works

Chen and Lin used a Wireless Sensor Network (WSN) to develop a system that recognizes standing-heat signal [6]. The system used a 3-axial accelerometer that recognizes the movements of the cows. The accelerometer is placed on the cow's forefeet. The authors utilized ZigBee and received signal strength indicator (RSSI) in achieving estrus detection.

Floresca et al. [7] presented a monitoring system called DISCOW to detect and observe mounting activities of cows. The system uses QR codes patches, high definition cameras, and a personal computer. When the QR code is blocked by the cow from mounting, the computer will analyze the detection and signals the camera to capture image, giving all the necessary information about in-heat cows.

By utilizing infrared cameras, Yuang, Lin, and Peng [8] developed a system that aims to recognize estrus detection at night using a non-contact video monitoring system. Image processing will be used to identify estrus-specific behaviors of dairy cows. The authors developed a video imaging technology that uses the length of the cows to detect estrus. A length of 2 cows shows specific mounting behavior and then a length of 1.5 cows will be the basis of the detected estrus.

In 2014, Tsai and Huang [9] introduced a motion and image analysis method for automatic detection of estrus and for monitoring mating behavior of a cattle. A region of interest for each video frame is analyzed where high levels of motion that has occurred. After analyzing video frames, foreground segmentation then follows. It separates the moving cow from the region of interest in each frame. By determining the changes of lengths between the moving objects, the following of cows and mounting behaviors are identified.

B. Feature Recognition using Scale-Invariant Feature Transform (SIFT) Algorithm

In computer vision, feature recognition refers to its ability to distinguish geometric features from images and classify them. These include distinct features such as eyes, mouth, chin, and other facial structures, which sets them apart from other objects. Face recognition algorithms and biometrics are one of the applications of feature recognition [10].

In 2004, Lowe developed Scale-invariant feature transform (SIFT) [11], an algorithm that extracts a set of unique points from gray-level images. From a gray-level image, a list of 2D points will be extracted. Each point is accompanied with a vector of low-level descriptors and thus, define a feature. These features are invariant in rotation, scaling, and in changes of illumination.

Detection of space-scale extrema, localization of key points, orientation assignment for each key points, and creating descriptors are the major steps in implementing SIFT. Fig. 1.shows an overview of the SIFT algorithm.

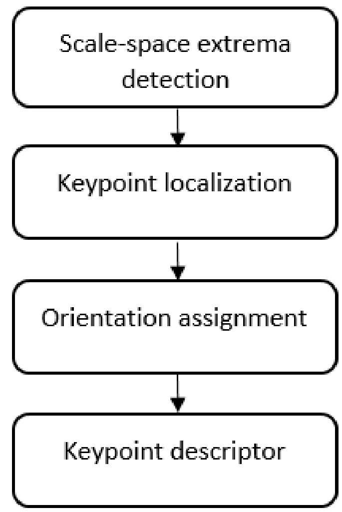

Fig. 1. Overview of SIFT Algorithm

Scale-space extrema detection identifies key points that are invariant to orientation and scale through the use of difference-of-Gaussian function (1).

$$D(x,y,\sigma) = \big(G(x,y,k\sigma) - G(x,y,\sigma)\big) * I(x,y) \quad (1)$$

Key points are highly selected based on their stability measures. To get accurate key point localization, a second order Taylor-series expansion is implemented (2).

$$D(x) = D + \frac{\partial D^T}{\partial x} + \frac{1}{2}x^T\frac{\partial^2 D}{\partial x^2}x \quad (2)$$

After the selection of key points, it will be assigned in a consistent orientation based on the properties of its local image (3). By using histogram of orientation, descriptors will be created. Lastly, features will be extracted using SIFT.

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\theta(x,y) = \tan\left(\frac{\big(L(x,y+1)-L(x,y-1)\big)^2}{\big(L(x+1,y)-L(x-1,y)\big)^2}\right) \quad (3)$$

C. K-Nearest Neighbor (KNN) Machine Learning Algorithm

The *k*-nearest neighbors (KNN) is a machine learning algorithm that is commonly used in, but not limited to, classification problems. The KNN algorithm works by storing all available cases and classifies new available cases by a majority vote of its k neighbors. Measuring the distance by a distance function will assign the case to a class that is most common among its K nearest neighbors [12].

Euclidean distance (4), Manhattan distance (5), and Minkowski distance are used for continuous functions (6), while Hamming distance is used for categorical variables [12].

$$d=\sqrt{\sum_{i=1}^{k}(x_i-y_i)^2} \tag{4}$$

$$d=\sum_{i=1}^{k}|x_i-y_i| \tag{5}$$

$$d=\left(\sum_{i=1}^{k}(|x_i-y_i|)^q\right)^{1/q} \tag{6}$$

III. METHODOLOGY

A. Data Gathering

A total of 23 Holstein cows were registered and monitored in the system starting November 2017. The system was deployed, tested and evaluated in Dairy Training and Research Institute of University of the Philippines – Los Baños.

B. Hardware Development

The barn has the dimensions of 15.2 meters in length, 5.8 meters in width, 3.80 meters in height and 88.16 square meters in area. Four high definition cameras were placed on top of the barn and are 3.85 meters apart. In Fig. 2, an equation was derived in determining the camera focal length.

$$Focal\ Length = \frac{Sensor\ Size\ x\ Working\ Distance}{Field\ of\ View} \tag{1}$$

$$Focal\ Length = \frac{4.8\ millimeters\ x\ 3.8\ meters}{5.8\ meters}$$

$$\mathbf{Focal\ Length = 3.14\ mm}$$

$$Focal\ Length = \frac{3.6\ millimeters\ x\ 3.8\ meters}{3.85\ meters}$$

$$\mathbf{Focal\ Length}$$

$$\mathbf{= 3.55\ mm}$$

Dimensions in mm			
Sensor	W	H	D
1/4”	3.6	2.7	4.5
1/3”	4.8	3.6	6
1/2”	6.4	4.8	8
1/1.8”	7.1	5.4	9
2/3”	8.8	6.6	11
1”	12.8	9.6	16

Based on the computation, the focal length to be used should be less than 3.14 mm and 3.55 mm. The smaller focal length that is available is 2.8 mm.

The system was composed of IP cameras, laptop, and the GSM module. The Starvis Vesper IP camera serves

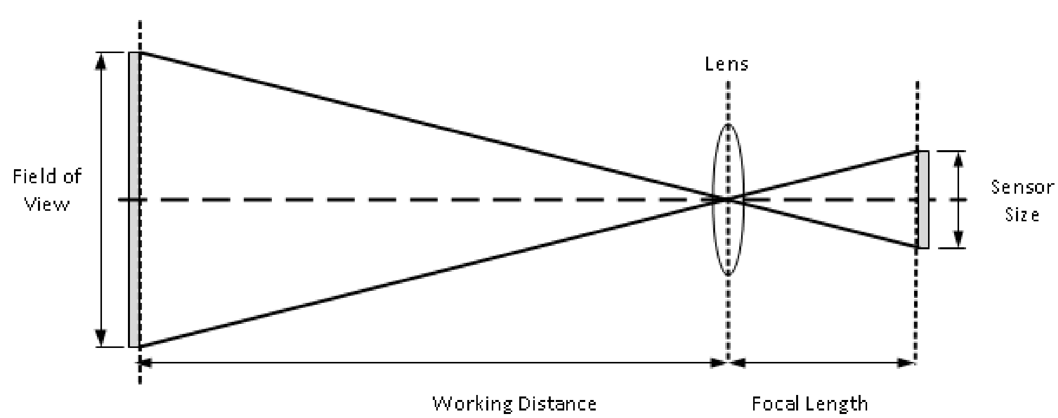

Fig. 2. Simplified Ray Diagram

as the input device of the system. It detects the cows and standing heat.

The laptop used in this study ran on is 64-bit Windows 8.1 operating system with an Intel Core i5 series 3rd generation (2.80Ghz) processor for the Central Processing Unit (CPU) along with a 4 GB RAM.

The GSM module used is the A6 mini with a working frequency between 850-1900 MHz and an Arduino UNO. The Arduino UNO was connected to it as the controller of the notification system.

C. Software Development

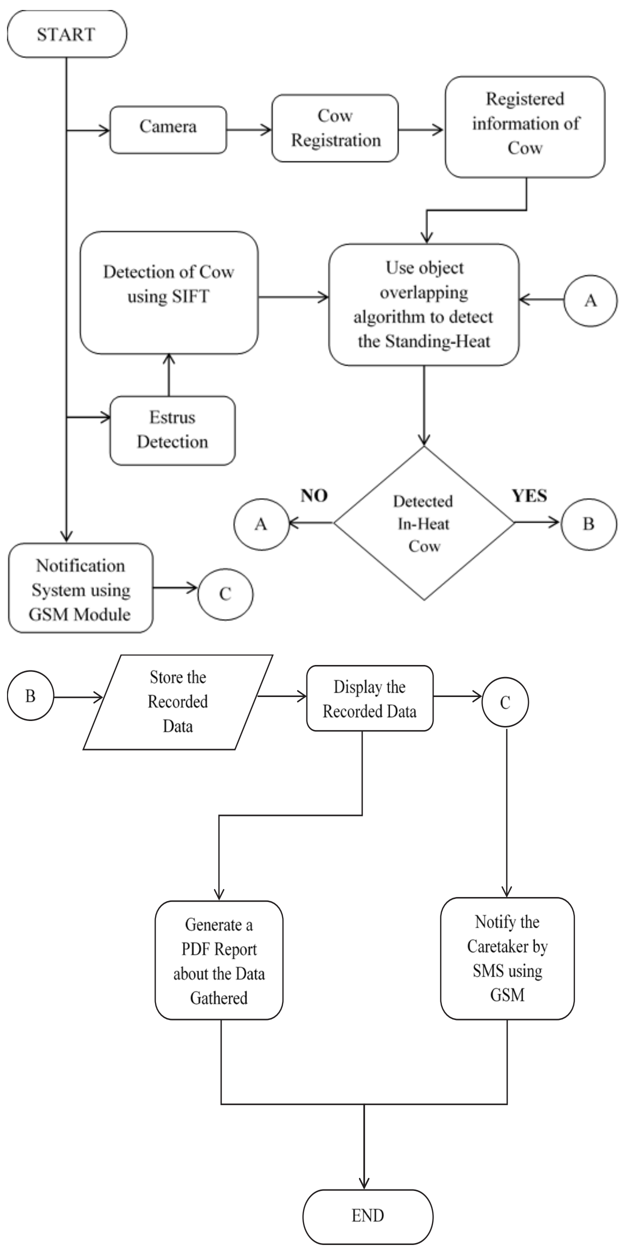

Fig. 7. System Program Flow Process

The camera of the system was used to capture live video feed of cows in the barn. It was used to detect and identify the cows inside the barn. The XAMPP application was first opened to give the access to the main GUI where the user must log in. Upon logging in, the cows top view image and its data information (like; date and time of registry, and ID) will be inputted by the user in the Register New Cow Menu. Such image is also known as a Model that will be used for identifying, tracking and detecting the cows that has been registered in the system. Each Cow that has been registered inside the barn will have its own identity in the system and will be named by the number imprinted on their back.

Using SIFT feature extraction, the cows will be detected by their different assigned pattern on the system. The number of Models in the registry will determine the accuracy of the detection. Afterward, the system will initialize the FLANN matcher that performs a K-Nearest Neighbor search. Consequently, the system will evaluate the features if it is a good match or not. The standing-heat will be detected by the overlapping of two cows' detection. If the threshold reaches three to seven seconds, the system will record the threshold and simultaneously alert the caretaker of the barn using the GSM module that a cow is set to be inseminated.

The GSM module will send a text message that a certain cow had a standing heat. The data of the standing-heat will then be stored in the database. A PDF file of the gathered data containing information of the said standing-heat that is stored on the database is ready to be printed out for the user's copy. A log file of all the standing heat image captured is also generated as well as a tabulated data under the Cows Detected Menu. A Print All option is also provided to allow the user to print out the said data in PDF file.

IV. Result and Discussion

The traditional way of monitoring estrus or standing heat in cows gives relatively high probability of not getting the optimum time for artificial insemination. The use of Cow In-heat Monitoring System has been implemented to be an an alternative way in monitoring standing heat that is both easy and precise.

A. Actual Testing Result for November 2017

The summary of the standing heat of test cows for the month of November was shown in Figure 8.

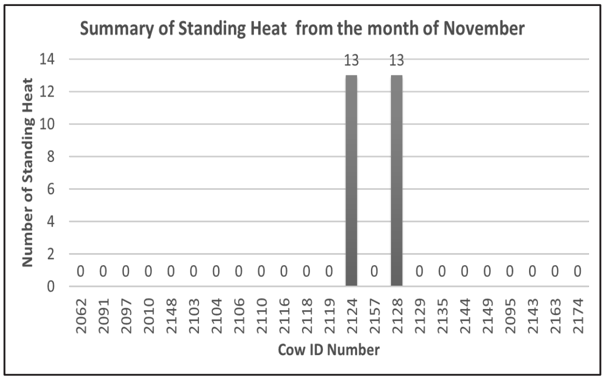

Fig. 8. Graphical Representation of Database Result for the month of November

Based fom Figure 8, test cow # 2124 and 2128 have 13 standing heatshence considered as considered "in heat."

Fig. 9. Example of detected standing heat

Fig. 9 shows an example of detected standing heat where 2128 mounted 2124. The box indicates the overlapping of one subject to other.

B. Actual Testing – December 7, 2017

The summary of standing heat from the month of December was shown in Fig. 10.

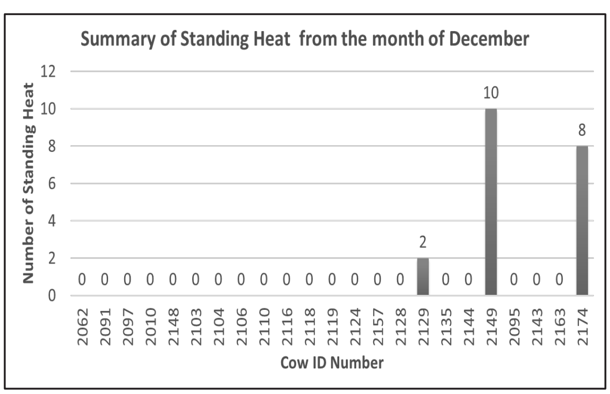

Fig. 10. Graphical Representation of Database Result for the month of December

Based on the graph shown, subjects 2149 and 2174 have showed more than six (6) mountings, therefore subject 2149 and 2174 were considered in heat. Subject 2129 was not considered in heat due to lack of number of mountings.

Fig. 11. Example of detected standing heat

Fig. 11 shows an example of detected standing heat where 2149 mounted 2174. The box indicates the overlapping of one subject to other.

C. Actual Data – January 11 & 19, 2018

A graphical representation for the summary of standing heat from the month of January was shown in Fig. 12.

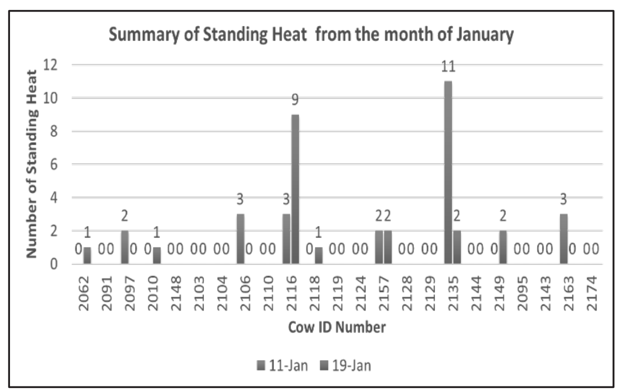

Fig. 12. Graphical Representation of Database Result for the month of January

Subjects 2116 and 2135 have showed more than six (6) number of mountings, therefore considered in heat. The subjects 2062, 2097, 2010, 2106, 2116, 2118, 2157, 2149 and 2163 were not considered in heat due to lack of number of mountings.

Fig. 13. Example of detected standing heat

Fig. 13 shows an example of detected standing heat where 2163 mounted 2135. The box indicates the overlapping of one subject to other.

D. Summary of Detected Mountings

The summary of detected standing heat starting from the month of November 2017 up to the month of February 2018 was shown in Fig. 14.

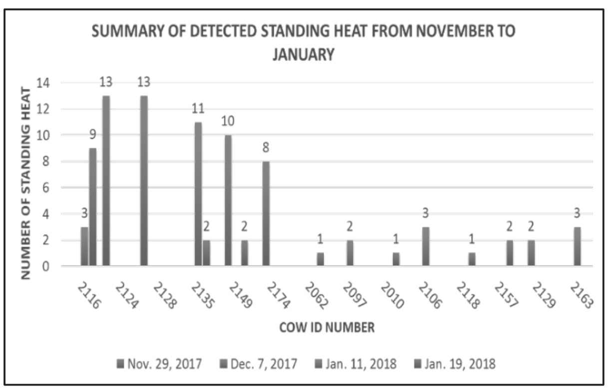

Fig. 14. Summary of Detected Standing Heat.

Fig. 14 shows all the cows that showed standing heat during the actual testing happened on November 29, 2017, December 7, 2017, January 11 and January 19, 2018. According to the table, subjects 2124, 2128, 2149, 2174, 2116 and 2135 were considered in-heat because these have more than six (6) mountings. Subjects that have showed less than six (6) standing heat were not considered in heat.

V. Conclusions

The Automated Cows In-Heat Detection and Monitoring System Using Image Recognition with GSM Based Notification System whose core system is image recognition for estrus detection, focused on identification, tracking, and detection of in-heat cows that is important for breeding purposes.

Through this project, the end-users were able to: (1) utilize the software XAMPP for the web-based graphical user interface, MySQL, and Python that uses the OpenCV module for the image recognition to detect the in-heat cows; (2) utilize IP cameras to monitor the movements of the cows; (3) receive notifications through GSM module where it sends an alert message that an in-heat cow has been detected; and (4) verify the actual tests of the automated system with 100% detection success rate.

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