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Automatic Swine Detection and Counting Using Hybrid Filter and Ellipse Fitting Model

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Abstract:

Over the past years, the use of technology has become ubiquitous in different organizations involving business ventures. The advent of imaging and database technology has made business owners to be motivated to integrate automation to their business operation (i.e. from small businesses to large enterprises). Swine or hog raising, for example, is a very popular enterprise in the Philippines, whose challenges in production monitoring can be addressed through technology integration. Swine production monitoring can become a tedious task as the enterprise goes larger. Specifically, problems like delayed and inconsistent reports are most likely to happen if counting of swine per pen of which building is done manually.

In this study, we present smartCount, which aims to ensure efficient swine detection and counting that hastens the swine production monitoring task. We introduce a method that automatically detects and counts swine based on Sobel filter with 8-neighborhood implementation and ellipse fitting model, given the still photos of the group of swine captured in every pen. Furthermore, the system can generate periodic production reports and can identify the specific consumables to be served to the swine according to schedules.

Keywords— **ellipse fitting model, Sobel filter, hybril filter, morphological operation, swine detection and counting, swine production monitoring.**

I. INTRODUCTION

Swine raising is a very popular enterprise in the Philippines such that there is a spread of vast amount of farm producers, which dominate the swine industry and other commercial sectors. Because of its large scale in nature, swine producers thoroughly and carefully manage and monitor the production. Swine production monitoring can become tedious task as the enterprise goes larger. People involved in production monitoring, experienced time delays and data inconsistencies in preparing the reports. As a result, creation of appropriate technology or system becomes apparently invaluable to farmers and the would-be swine producers. Such system can be introduced to them in order that they may realize profitable production and improve their quality of life (1).

There are number of phases that swine can be separated logically. These include *farrowing, weaning, nursery care and grower-finisher* phase. Farrowing is a process where sows give birth to piglets. Prior to this process, the sows are usually transferred to a farrowing room where they farrow piglets of about 8 to 16 (2). After weaning, pigs are normally brought into a nursery room where the environment temperature is controlled and on a slotted floor. At the age of 6 to 10 weeks, they are then taken out from the nursery and transferred to a grown finisher area or building. While staying in such place, pigs are being fed with the right amount of feeds until they reach 230 to 275 pounds of market weight and ready to be sold. Producers calculate the total harvest of their swine production from birth to becoming grower. The remaining or the survival pigs are the once considered the total harvests, which entered the grower-finisher phase (2).

The conventional method of counting the total harvest is tedious and time consuming. Continuous counting of hundreds of pigs per day may lead to eye fatigue, which in turn affects the accuracy of results. Specifically, manual counting may result to significant delay and inconsistency of swine production and monitoring. Furthermore, it may result to the postponement of preparing updated daily reports and difficulty in monitoring what kind of feeds and supplements should be given in which swine over a period of time. Automatic swine detection and counting that is objective, reliable and reproducible in nature may considerably reduce these problems. There has been considerable amount of researches being made on object counting using image processing, but most of them work for automatic tracking and are not applied in swine production monitoring. One important stage in swine detection is the edge detection in each object found in an image; and one of the tools that is widely used is the Canny algorithm. However, Canny is computationally more expensive (3-5) compared to other operators; hence, leveraging Sobel filter as part of detection module is apparently invaluable and is being used in this paper.

Our study generally aims to develop a system that can automatically detect and count the number of swine in a particular pen and consequently provides immediate swine production periodic reports. Furthermore, it has the capability to determine the kind of consumables that should be given to the swine over the span of time. It also addresses problems on significant delays and inconsistency of swine production and monitoring. Since our work involves image inputs, pre-pre-processing of the captured images is a pre-requisite for swine detection stage so that swine are properly detected and counted, thereby ensuring efficient generation of reports is ensured. This, in turn, can contribute significantly for a better and faster swine production monitoring and less workload in the part of the caretaker.

II. METHODOLOGY

A. *smartCount: an Overview*

Our work performs swine production monitoring by doing automatic swine detection and counting as a prerequisite task. We capture images (i.e. still photos) of the group of swine located in each pen with appropriate light illumination in order that each side attains similar amount of lighting. The camera captures the swine image in a top view position at 180 degrees. Such position is very convenient as it covers the entire pen and it can visibly detect the swine in its ellipse shape. Fig. 1 presents the general view of the proposed system on how the camera is mounted. Images captured are stored in the image database.

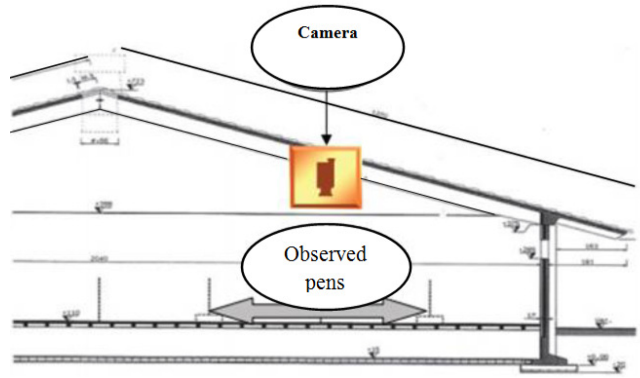

Fig1. General view of the system.

Fig. 2 shows the proposed framework for automatic swine detection and production monitoring system. To begin the process, raw images from the image database is extracted or retrieved. Dimension alignment and image resizing is then performed, followed by the pre-processing of images to enhance contrast and remove undesirable image noise. This is done by converting the captured image into a grayscale form and applying Median filtering technique. After which, we utilize Sobel operator for proper edge detection and segmentation purposes.

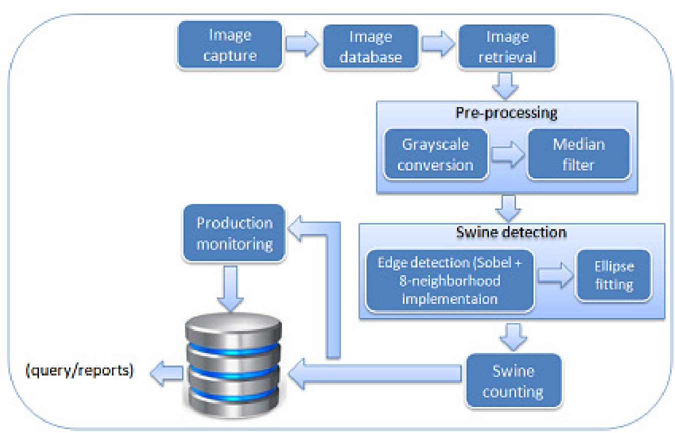

Fig. 2 Framework of the Proposed System

To further improve the segmentation process, an 8-neighborhood rule was implemented. We call such processes as hybrid filter as it leverages Sobel and 8-neighborhood rule implementation (i.e. morphological operation) to improve the performance of multi-swine segmentation. Empirical results show that Canny algorithm is computationally more expensive compared to other operators (3-5). Thus, exploring the advantage of Sobel along with the morphological operation may reasonably address this limitation. Lastly, ellipse fitting algorithm is then applied to identify swine. After swine detection, we utilized the ellipse fitting model introduced by Cuevas et al. (6) for multi-ellipse detection and consequently, the system returns the number of swine detected. Data generated are then saved in the database.

B. Overview of Sobel Filter and Ellipse Fitting Model

B.1. Sobel Filter

Sobel Filter, also known as Sobel operator, is widely used in the area of image processing and pattern recognition, specifically in detecting edges of objects in a captured image. For each pixel position in an image, the image gradient is calculated, where the magnitude of the vector Δf is defined as,

$$\Delta f = mag(\Delta f) = \sqrt{G_x^2 + G_y^2} \tag{1}$$

where G_x represents the x direction and G_y represents the y direction.

The idea here is that, in every point, Sobel filter computes the gradient of the image intensity, which gives the direction of having a huge increase from light to dark as well as the change rate in that direction. Mathematically, the gradient of a two-variable function (i.e. the image intensity function) is at each image point of a 2D vector with the components given by the derivatives in the horizontal and vertical direction. The Sobel masks of 3x3 size is presented in Table I.

Table I
Sobel Masks (3X3)

For x-direction (horizontal mask)

-1	-2	-1
0	0	0
1	2	1

For y-direction (vertical mask)

-1	0	1
-2	0	2
-1	0	1

The horizontal mask approximates the partial derivative in the x-direction, and the difference between the third and first columns in the other mask approximates the derivative in the y-direction. After computing the partial derivatives with these masks, we obtain the gradient's magnitude as before.

When the horizontal mask is convolved onto an image, it projects horizontal edges in it. Additionally, it calculates the difference among intensities of pixels of a particular edge (7). As the center row of mask contains zero values, it does not include the original values of edges in the image, but it does compute the difference between the above and below pixel intensities of a certain edge, which results to the increase of the sudden change of intensity values, thereby making the edge much clearer or visible. When the vertical mask of Sobel filter is applied on the image, it projects vertical edges in it. To put it simpler, it works like a first order derivative and computes the difference of pixel intensities in an edge region. As the center column of mask contains zero values, it excludes the original values of an image, but instead, it calculates the difference between left and right pixel intensities around the edge. This, in a way, provides more weight age to the pixels around the edge region, thereby intensifying further the edges.

B.2. Ellipse Fitting Model

In real images, ellipse is considered to be one of the most widely used geometric shapes. In fact, in computer vision and pattern recognition, the ellipse extraction from the given images has been considered an interesting problem. Several approaches were proposed, which fall under different categories, namely, Hough transform-based (HT) (8), Symmetry-based (9), , Simple Linear Operator (11) and Random Sampling (10). Most of these methods, however, are computationally expensive and does require large amount of memory for a sub-pixel resolution to be obtained (6).

In this study, we exploit the advantage of the Collective Animal Behavior (CAB) algorithm introduced by Cuevas et al. (6) to extract multiple ellipses from an image. In (6), an evolutionary algorithm is employed to mimic the way animals collectively behave u the assumption of having the general detection process being a multimodal optimization problem. The CAB algorithm performs tasks under the assumption that the set of operations having similarities with the rules of interaction that model the collective behavior of animals do exist.

In their proposed method, the search agents perform emulation of a group of animals, which interact with one another with the use of the biological rules modeled as evolutionary set of operators. Such detector utilizes parameters combining five edge points so that the optimum solutions for extracting ellipse candidates are identified, while a matching function is used to determine if the ellipse candidates being identified are found in the actual image. Using the evolutionary algorithm, the set of ellipse candidates are then evolved, based on the values of such matching functions so that the best candidates can be fitted into the actual ellipses found within the image. This is followed by an analysis to find the best ellipse as well as the significant minima or remaining ellipses (6).

To detect objects with elliptical shapes, an image has to undergo pre-processing that gives a single-pixel edge image. Then, the (x_i, y_i) coordinates for edge pixel p_i are stored inside the edge vector $P=\{p_1, p_2, ..., p_{Tp}\}$ where T_p is the total number of edge pixels.

Each ellipse candidate E_c utilizes five edge points p_s, p_t, p_u, p_v *and* p_w $(Ec=\{$ *points* $p_s, p_t, p_u, p_v, pw \})$. Similar to the work of Cuevas et al. (6), we perform substitution of coordinates of each point of E_c into equation (2) in order to find a set of five simultaneous linear equation using the 5 unknown parameters q', r', s', v' *and* w'.

$$q'x^2 + 2h'xy + r'y^2 + 2w'x + 2v'y + s' = 0 \qquad (2)$$

Then, solving the involved parameters and dividing by the constant c', it yields:

$$qx^2 + 2hxy + ry^2 + 2wx + 2vy + 1 = 0 \qquad (3)$$

Considering the edge points configuration as shown in Fig. 3, the center of the ellipse (x_0, y_0), the maximum radius ($rad_{\max}$), the minimum radius (rad_{min}) and the ellipse orientation (θ) can be computed through equations (4)-(8).

$$x_0 = \frac{hv - rw}{C} \qquad (4)$$

$$y_0 = \frac{wh - qv}{C} \qquad (5)$$

$$rad_{max} = \sqrt{\frac{-2\Delta}{C(q + r - R)}}, \qquad (6)$$

$$rad_{min} = \sqrt{\frac{-2\Delta}{C(q + r + R)}}, \qquad (7)$$

where

$$R^2 = (q - r)^2 + 4h^2 \text{ and } C = qr - h^2 \qquad (8)$$

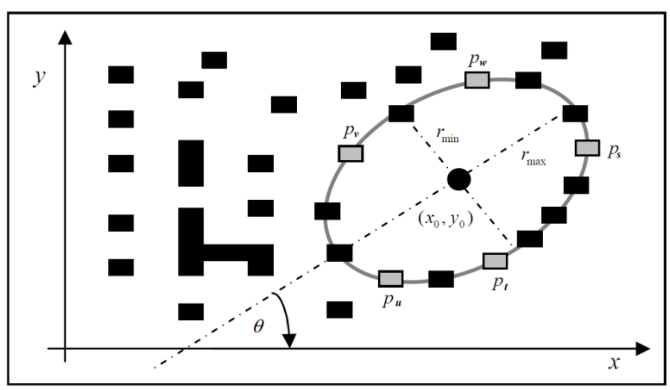

Fig. 3 Ellipse candidate generated from the combination of points p_s, p_t, p_u, p_v *and* p_w using Cuevas et al approach (6).

C. Context-Diagram and USE CASE of the proposed system

As our study include database creation and manipulation for swine production monitoring, context and use case diagrams both play a significant role during the design and development of the system. Our context diagram presents the bird's eye view of the swine counting and production monitoring system. It defines the boundary between the system and its environment, showing the entities that interact with it. Fig. 4 presents the context diagram of our proposed system. The diagram clearly depicts that updates can originate either from the management or caretaker. The system can automatically perform the monitoring of activity like supplying of feeds and supplements in a given span of time.

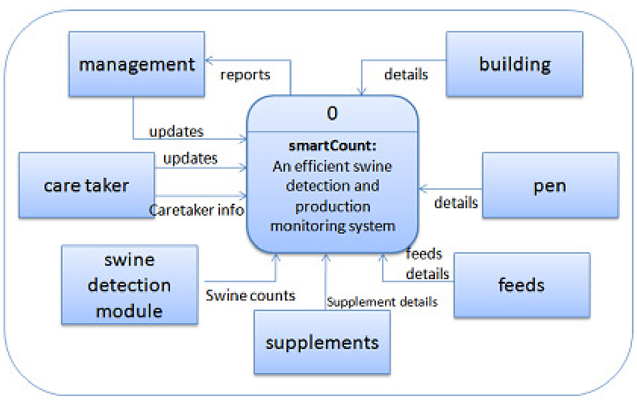

Fig. 4 Context Diagram of smartCount

The USE case diagram at its simplest form, is a representation of a user's interaction with the system that shows the relationship between the user and the different actions or event steps, which typically defines the interactions between an actor and a system, to achieve a goal. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well.

Fig. 5 shows the Use-case diagram, which represents each user's (e.g. the owner and the caretaker) interaction with the system. In this figure, the user's function is recognized. The owner, for example, can do monitoring and updates on the system. Both of them can login and view the system. Clearly, the owner is capable of managing the entire system (e.g. adding of pens, viewing of reports, etc.). The caretaker is responsible of managing reports, monitoring system and monitoring the condition of the swine.

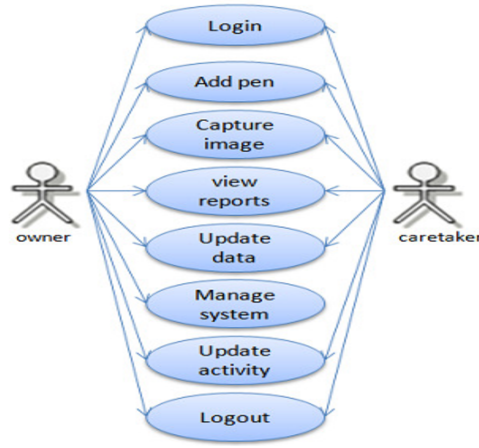

Fig. 5 USE CASE Diagram

III. Results and Discussion

In our experiments, 142 images of swine were taken from 16 pens (with varied number of swine per pen) of Jerasenes Piggery Farm located at Awang, Opol, Misamis Oriental, Philippines. Thorough experiments and quantitative analysis was conducted to test and evaluate the efficiency proposed method in automatic swine counting and generation of production reports. In particular, we evaluated the system using the three performance measures, such as precision, recall and accuracy rate of different methods like Canny and Prewitt-based approaches and compared them to our proposed approach. In other areas like information retrieval and pattern recognition with binary classification, precision is defined as the fraction or part of the instances being retrieved, which are considered relevant, while recall or sensitivity is defined as the fraction or part of relevant instances, which are retrieved.

Figures 6 and 7 show some sample results of the experiments we performed using different methods for segmentation as pre-requisites for swine recognition and counting. Notice that our approach yields an accurate result in counting the number of swine in a particular pen as evident in Figure 7c. Figure 8 presents the sample outputs when performing some tasks throughout the system. Figure 8a shows the sample main form. When the user clicks the 'capture and count' button, he will be redirected to a new window as presented in Figure 8b, while Figures 8c and 8d present the sample screenshots when a user clicks 'view activities' and 'annual reports' buttons, respectively. More sample results when applying our algorithm for swine detection and counting are presented in Fig. 9.

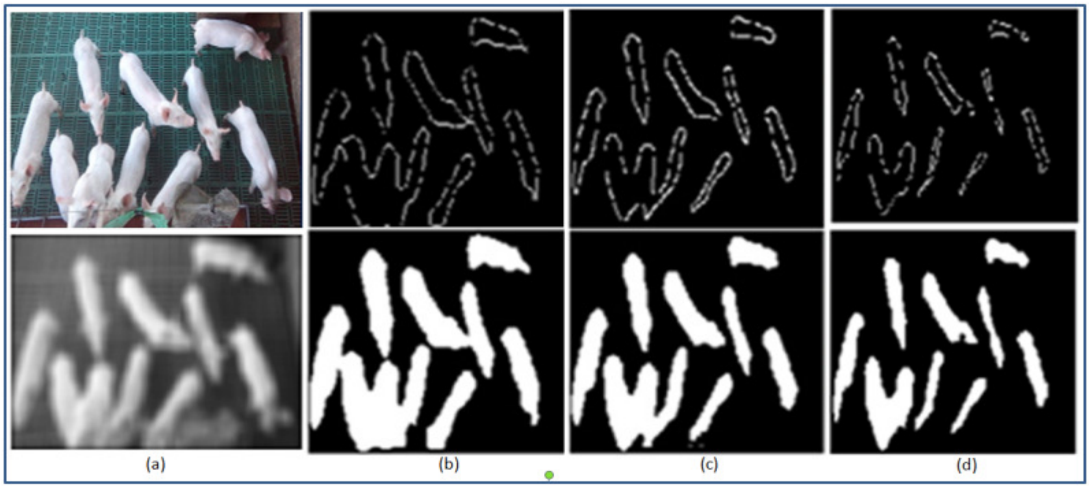

Fig. 6 Pre-processing and edge detection and segmentation results. (a) original image and result of noise removal using median filter, (b) Prewitt method, (c) Canny method and (d) our approach - Sobel filter + 8-neighborhood implementation

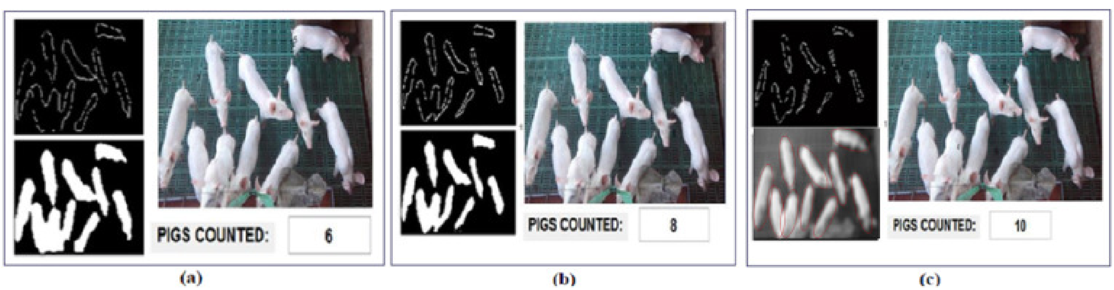

Fig. 7 Sample results for swine detection and counting using different approaches for detecting edges (a) Prewitt edge detection, (b) Canny edge tool, (c) our approach (sobel + 8-neighborhood rule implementation + ellipse fitting).

Fig. 8 Screenshots of smartCount. (a) Main form, (b) sample output when 'capture and count' button is clicked, (c) sample screenshot when 'view activities' button is clicked and (d) sample annual reports for swine production monitoring

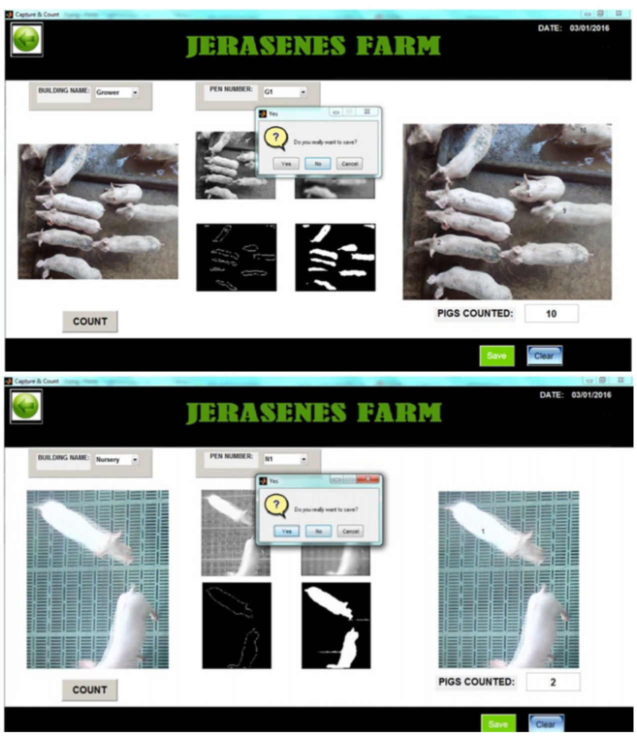

Fig. 9 Sample outputs when count button is clicked.

Table II shows the evaluation of precision and recall using different detection tools prior to the proper detection of swine. From the 142 captured images of swine, the results reveal that our approach is superior among others, which uses Prewitt and Canny as edge detection tools.

Table II

Comparison of the Performance of the Three Methods for Swine Counting

	Using Prewitt edge detection tool	Using Canny edge detection tool	Our approach (Sobel + 8-neighborhood + ellipse fitting)
Precision	80.0%	94.2%	97.0%
Recall	82.3%	91.6%	98.3%
Accuracy	93.7%	96.2%	98.0%

Prewitt-based swine detection method got a precision and recall of 80% and 82.3%, respectively, while Canny-based approach yields 94.2% and 91.6% of precision and recall, respectively. Our approach (i.e. applying Sobel filter plus the 8-neighborhood rule implementation, which applies morphological operation and ellipse fitting) appears to be superior as it resulted to a precision and recall of 97.0% and 98.3%, respectively. For the accuracy measures, the table reveals that Prewitt has an accuracy rate of 93.7%, while Canny has 96.2%, but our approach yields as far as 98.0% accuracy rate. Thus, experiments reveal that our approach is superior among other edge detection methods prior to employing ellipse fitting model for swine detection.

IV. Conclusion

In this study, we present an application using hybrid filter for automatic swine detection and counting for efficient swine production monitoring. We model the system based on the needs of

Jerasenes Piggery farm, which we discovered during the conduct of series of interviews. Our hybrid approach (Sobel + 8-neighborhood + ellipse fitting) provides efficient results of counting the swine automatically. One limitation, however, is that it is most likely to detect any ellipse-shape objects (e.g. ellipse-shape feeding rack, etc.), which may yield to unsatisfactory detection results. Nevertheless, our system generally shows several merits that pertain to real application. Firstly, it hastens the process of generating swine production periodic reports as it employs automatic detection and counting of swine per pen installed in each building; and secondly, the notification of what type of feeds and supplements to serve to the swine in a day, implies less workload in the part of the caretaker.

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