Image Technology based Cow Identification System Using Deep Learning

Thi Thi Zin, *Member, IAENG*, Cho Nilar Phyo, Pyke Tin, Hiromitsu Hama, Ikuo Kobayashi

***Abstract*— Today worldwide trending in precision dairy farming is becoming more focus on an individual cow welfare and health rather than group management by using modern technologies including image processing techniques. In such cases, individual cow identification is one of the fundamental ingredients for the success of modern dairy farming. Thus, in this paper we shall explore and examine how image processing technologies can be utilized in analyzing and identifying individual cows along with deep learning techniques. This system is mainly focus on the identification of individual cow based on the black and white pattern of the cow's body. In our system, firstly we detect the cow's body which have been placed on the Rotary Milking Parlour by using the inter-frame differencing and horizontal histogram based approach. Then, we crop the cow's body region by using the predefined distance value. Finally, the cropped images are used as input data for training the deep convolutional neural network for the identification of individual cow's pattern. The experiments are performed on the self-collected cow video dataset which have been taken at the large-scale ranch in Oita Prefecture, Japan. According the experimental result, our system got the accuracy of 86.8% for automatic cropping of cow's body region and 97.01% for cow's pattern identification. The result shows that our system can automatically recognize each individual cow's pattern very well.**

***Index Terms*—cow identification, deep learning, edge detection, horizontal histogram**

I. Introduction

The demand for the automatic monitoring system of cow in livestock farm is increasing year by year due to the increasing amount of cow in large farm and the difficulty of hiring labor for monitoring the cows. In recent year, many systems have been proposed for the automatic monitoring and identification of the cows but most of the system need to put the sensor devices on the body of the cow which can cause the burden for the cow. The identification of the cow's using Radio Frequency IDentification (RFID) technology [1] is an affective method for the recognition and identification each individual cow but it need to attach the RFID tag on the ear of the cow which can cause stress on the cow. Eventhough, the cow identified by the RFID, there still need the labor for the continuous monitoring the health of each individual cow. Another disadvantage of the traditional identification systems is that they are expensive and unreliable.

The visual based automatic health care and monitoring system for the cow can solve those problems by minimizing the burden of the labor by automatic monitoring from the video data. For the implementation of automatic health monitoring system for cow, the recognition of each individual cow plays as an important role because there is necessary to monitoring the behavior of each cow for long term such as monitoring the body condition score of the cow which has great impact on the health condition of each cow. Therefore, our proposed system of individual cow pattern identification is very useful for the automatic health care monitoring of the cow without burdening both for the labor and the cow side. The proposed system is low cost because it can reduce the cost for hiring labor and not need to use the sensor device on each cow.

This paper is organized as follow. Some related works are presented in section 2. The detailed proposed system is explained in section 3 following by the experimental results in section 4. Finally, in section 5, the conclusion and some future works are discussed.

II. Some Related Works

In this session, we will describe about some research works of the cow's identification system. The cow identification system based on the iris analysis and recognition have been proposed in [2] for enhancing the cow management in cows' traceability system. In that proposed system, the authors firstly assessed the image quality of capture iris sequences and selected the clear iris. Then, the inner and outer boundaries of cow's iris are fitted as ellipse form by using edge detection based segmentation. Then normalized the iris image using geometric method and 2D complex wavelet transform is applied to extract the local and global features of the cow's iris. This method can have a lot of limitation in real-world uncontrollable environment because of the difficult of getting the clear and good iris image of the cow.

The authors in [3] proposed the robust cow identification scheme from the muzzle print image using the Scale Invariant Feature Transform (SIFT) for detecting the interesting point in pattern matching. Then the Random Sample Consensus (RANSAC) algorithm is applied over the SIFT output in order to remove the outlier feature points for the robust system.

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Thi Thi Zin is with Department of Electrical and System Engineering, Faculty of Engineering, University of Miyazaki, Miyazaki, JAPAN. (corresponding author, phone: +81-985-58-7411; fax: +81-985-58-7411; e-mail: thithi@cc.miyazaki-u.ac.jp).

Cho Nilar Phyo is with Department of Materials and Informatics, Interdisciplinary Graduate School of Agriculture and Engineering, University of Miyazaki, JAPAN.

Pyke Tin is with International Relation Center, University of Miyazaki, JAPAN.

Hiromitsu Hama is with Graduate School of Engineering, Osaka City University, JAPAN.

Ikuo Kobayashi is with Field Science Center, Faculty of Agriculture, University of Miyazaki, JAPAN.

They got the identification accuracy of 93.3% with reasonable processing time. This system got the high accuracy with fast processing, but there still have one limitation of getting the muzzle print image of each cow at the time of identification which is a difficult task for automatic monitoring system.

The cows' identification system using ear tag was proposed in [4]. In this system, the authors used the color threshold approach for cow region detection and Hough transform based flood fill method for segmentation. For the recognitions task, the author applied the template matching method, k-nearest neighbor and support vector machine for Optical Character Recognition of the ear tag. The authors describe their proposed system can handle 98% of the digits by using the good data and k-nearest neighbor method. In [5], the computer vision based individual Holstein cattle recognition is proposed by imaging the cattle's body pattern which are captured by the charge-coupled devices (CCD). Firstly, the pixel values of the cattle body images are transform into the data which composing with binary signals for the neural network input. The images of 49 cattle are used to analyze the input layer and 10 images are used to analyze the output layer elements of the neural network. The author proved that the proposed system can generate the reliable recognition of individual pattern under the natural lightening condition.

III. PROPOSED SYSTEM

The proposed system for individual cow identification consist of two main components. The first one is the automatic detecting and cropping of the cow's body region using inter-frame differencing and horizontal histogram based approach. The second component is the training of deep convolutional neural network over the cropped cow's pattern images for the identification of the individual cow's pattern. The overall system flow of the proposed system is shown in the Fig. 1.

A. Automatic Detecting and Cropping Cow's Body Region

The process flow of automatic detecting and cropping of the cow's body region is shown in Fig. 2. For detecting the cow body region, firstly we perform the inter-frame differencing between two consecutive frames of cow's video in order to detect the moving pole location. Then, we transform the inter-frame differencing result into the binary image by using the predefined threshold. The equation of inter-frame differencing method based binary image creation is described in equation (1).

$$M_t(x) = \begin{cases} 1 & \text{if } \left| I_t(x) - I_{t-1}(x) \right| \geq \text{Threshold}, \\ 0 & \text{otherwise}. \end{cases} \qquad (1)$$

where

$M_t(x)$ is the result binary image of frame t,
$I_t(x)$ is the cow's image at frame t and
$I_{t-1}(x)$ is at the previous (t-1) frame.

Then, we count the frequency of the occurrence of white pixel in the horizontal direction of each point along the vertical axis. As a result, we got the horizontal histogram of the binary image. The size of each frame is 1024×768 and we use the white pixel occurrences (350 pixels) as a Threshold in order to find the pole location. If the horizontal histogram count is greater than Threshold, we regard that location as pole location. If two poles' location are detected, we use the location which is located near the previous detected pole. The binary image and horizontal histogram of different pole location are shown in Fig. 3.

For cropping, we use the cropping height and width by the fixed value of 400 pixels and 840 pixels, respectively because the distance between two poles location and the length of the pole are the same for all frames. After getting the pole location, we check it for finding the cropped direction. If the value of y coordinate of detected pole plus the cropped height threshold of 400 is less than or equal to the height of the original image, then cropping is performed over the lower 400 pixels' area of the cow's image, otherwise, the upper 400 pixels' area is cropped.

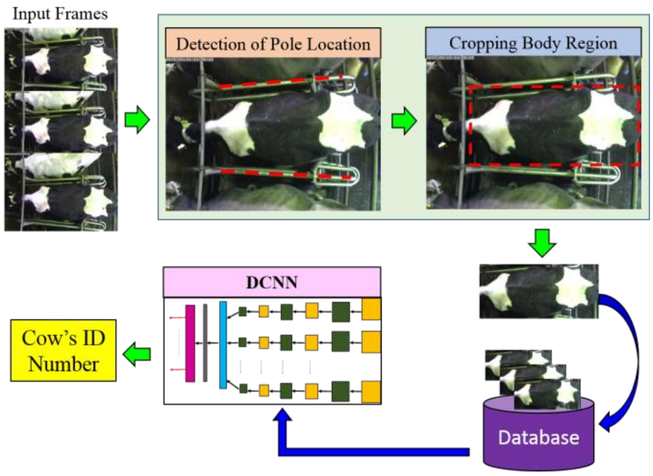

Fig. 1. Overall system for individual cow's pattern identification

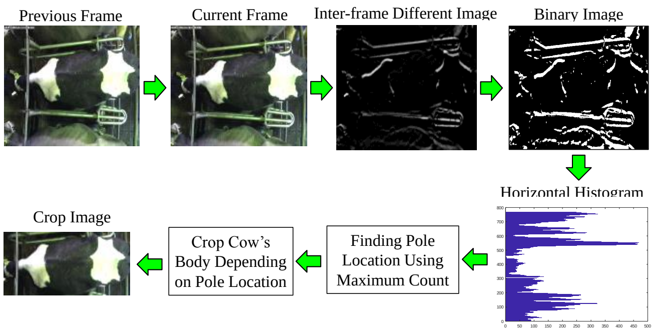

Fig. 2. Process flow of detecting and cropping body region of cow

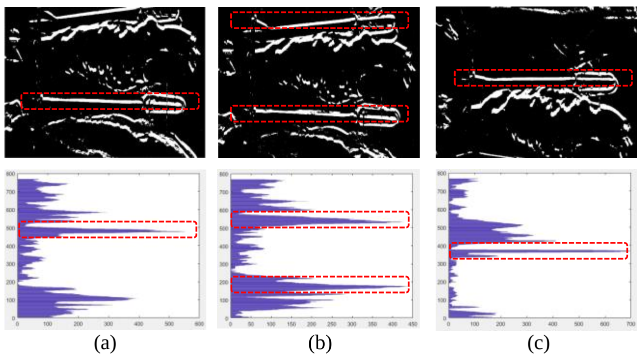

Fig. 3. Binary image and horizontal histogram result for

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(a) frame-608, (b) frame-617 and (c) frame-639

B. *Deep Convolutional Neural Network*

After cropping the cow's body region which include the black and white pattern for identification, we train them into deep convolution neural network which is a famous method for visual object recognition [6] and hand-written digit recognition [7] with superior performance among state-of-the art methods. We apply the deep convolutional neural network (CNN) over the cows' pattern of RGB color input images. The architecture of the DCNN is shown in Fig. 4.

In this architecture, there consists of 1 input layer, 3 convolution and max pooling layers, 1 fully connected layer and 1 output layer. The cow's pattern image of size 64×32×3 are used as inputs. In each hidden layer, there consist of three main operations such as convolution, max pooling and sigmoid activation function. The initialization of weight value of all layers done by the initialization with random number. The weight initialization methods, the filter size and the output feature maps of each convolution and max pooling layers are shown in Table.1. We also applied the randomly initialized weight vectors of size 100 at the fully connected layer and soft-max function is used at the output layer in order to calculate the probability of each possible cow's ID. The neural network is trained by using the backpropagation algorithm with stochastic gradient descent method. We used the learning rate as 0.0001 and the momentum value as 0.9. The network is trained with 1000 iterations by using the batch size of randomly selected 100 input images from the training dataset. The Caffe DCNN framework [8] is used for implementation of experiments.

IV. Experimental Results

For performing the experiments, we create our own cow's pattern dataset which consist of 45 different cows' patterns from the 22 days' video data taken from March 10, 2017 to March 31, 2017. The recording frame rate is 30 fps. The cow's pattern images of the first 15 videos are used as the training data and all 22 days' videos data are used as the testing data. The sample images of 45 different cows' pattern are shown in Fig. 5. The cow's pattern dataset consists of two challenges such as the rotation variation of cow's body and the day by day illumination changing condition. In our proposed system, we handle those two kind of challenges in order to able to apply the system under the rotation invariant and various illumination changing environment.

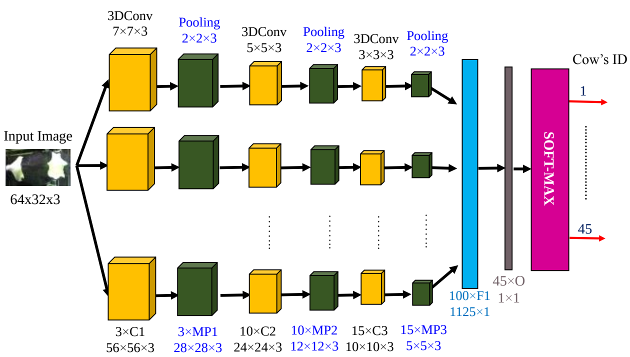

Fig. 4. Architecture of Deep Convolutional Neural Network

TABLE I. Parameters of DCNN

Layer	Filter Size	Weight Initialization Method	Feature Maps
C1	7×7×3	Normalized Uniform	3
MP1	2×2×3	-	3
C2	5×5×3	Normalized Uniform	10
MP2	2×2×3	-	10
C3	3×3×3	Normalized Uniform	15
MP3	2×2×3	-	15

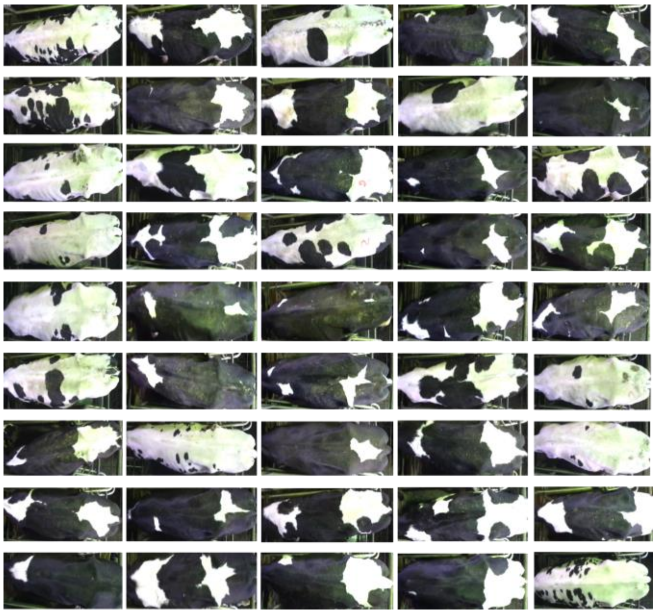

Fig. 5. Sample images of 45 cows' pattern (IDs are assigned from left to right and top to bottom order)

A. *Rotation Variation*

The cow's pattern images can include the rotation because the cows can move at the time of staying on the para for squeezing milk. The example of rotated cow's pattern images is shown in Fig.6. In order to get the rotation invariant feature from the DCNN, we use the 30 continuous frames of each cow's pattern as the input for training the DCNN.

B. *Illumination Changing Condition*

The illumination can change time by time, so the video data of the cow's pattern include the effect of the illumination changes. It means that the images of the same cow's pattern can be different depending on the illumination condition at the time of recording the video. The example images of the same cow's pattern under the different illumination condition is shown in Fig.7.

C. *Performance Evaluation*

We evaluate the performance of the system for both automatic detecting and cropping of cow's body region and the individual cow's identification accuracy. The average cropping accuracy for 22 days' videos data is 86.8 %. The accuracy of the identification on the training data set of 15 days' videos is 98.97% and on the testing data set of 22 days' videos is of 97.01%. The identification accuracy of each cow's ID for both training data and testing data are shown in Fig.8.

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V. Conclusion and Future Work

In this paper, we proposed the individual cow's identification using the inter-frame differencing and horizontal histogram based method for automatic detecting and cropping of cow's body region and the DCNN for training and recognition of cows' pattern. We also create the cows' pattern dataset of 45 different cows' pattern and perform the experiments on that dataset. The proposed system got the accuracy of 86.8 % for automatic detecting and cropping of cows' body region and 97.01% for individual cow's identification. In the future, we will try to improve the accuracy of automatic detecting and cropping of cows' body region by using enhancing histogram based approach and we will also analyze the performance of the system under the various evaluation methods.

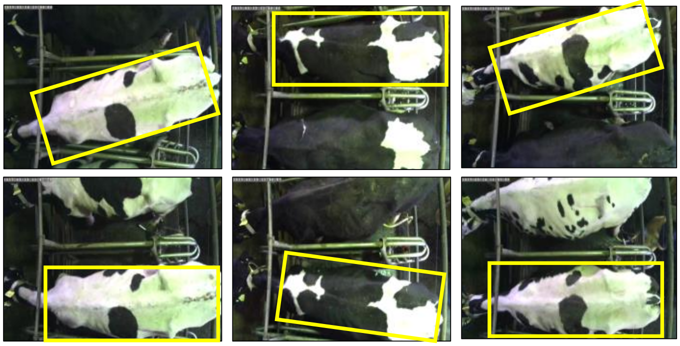
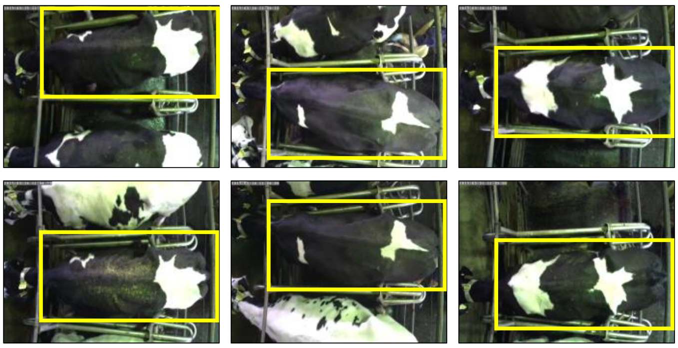


Fig. 6 Example of cow's pattern images under various rotation



(a) (b) (c)

Fig. 7. Example of cow's pattern images under various illumination condition: (a) ID-4, (b) ID-37 and (c) ID-42

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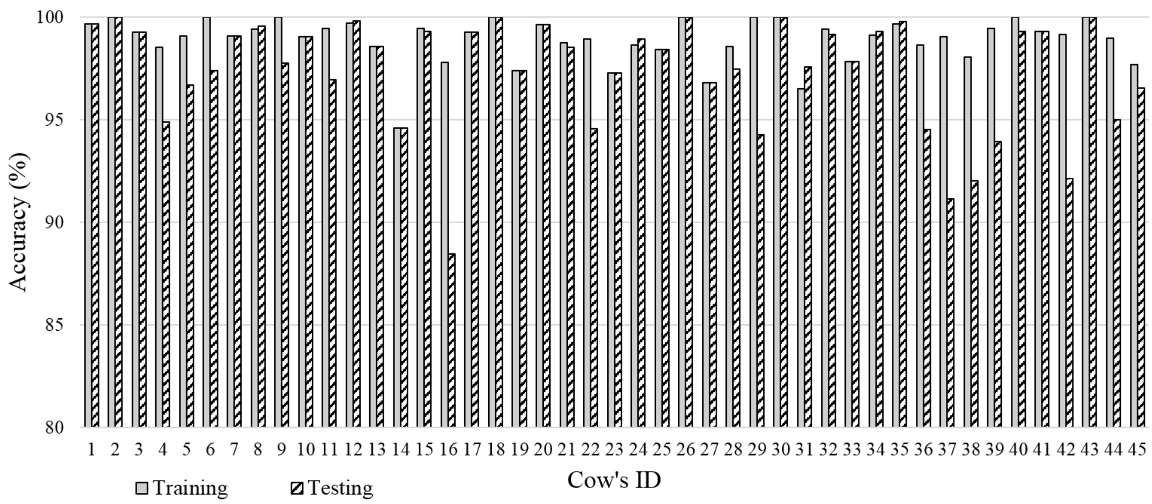

Fig. 8. Identification accuracy of individual cow

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