Analysis of Goose Body Temperature Using Convolutional Neural Networks

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***Abstract*— With the improvement of bio-security awareness and industrial scale, the poultry industry in terms of non-open and automation direction. The development of machine learning has also greatly increased the application range of convolutional neural networks in recent years. This study aimed at the location analysis of goose, including image capture system, position detection system, and body temperature monitoring. The image capture system uses the Raspberry Pi with a camera to upload captured images to a network attached storage device. The position detection system uses the Faster R-CNN convolutional neural network algorithm to create a graph for finding the location of the goose in the image. The temperature monitoring system uses the position of the goose obtained by the body temperature integrated position detection system measured by the thermal imager to instantly find the body temperature of the goose. It is expected that the future can be based on this research to achieve the goal of disease warning.**

I. Introduction

The breeding facilities of the Taiwanese waterfowl industry have traditionally been dominated by open-ended poultry houses. This method of raising poultry is susceptible to pathogens caused by wild bird droppings and feathers. The outbreak of bird flu that began in 2015 has caused great damage to the waterfowl industry.

The cause of the outbreak of avian flu can be divided into three parts: (1) The virus spreads rapidly by migratory birds and resident birds, (2) the feeding facilities of different poultry species are too close, because the geese have no obvious symptoms. If the bird flu epidemic is discovered and notified later, it is easy to cause losses in the surrounding poultry farms, and (3) most of the traditional poultry farms use low-cost open poultry houses, which leads to an increase in the chances of feeding the geese to the pathogens.

In order to improve the rapid spread of diseases caused by open poultry houses, the government has vigorously promoted the popularization of open poultry houses in recent years. Compared with the open type, the non-open poultry house can greatly reduce the chance of contact between the breeding birds and the wild birds in the facility to enhance the biosafety in the poultry house.

In the case of avian disease, obvious clinical symptoms of crouching, diarrhea, and feather wrinkles are often found. In order to observe whether the birds have abnormal behaviors due to illness, in the traditional breeding management of the waterfowl industry in Taiwan, people enter the on-site poultry house to observe the living conditions of the birds. However, because the goose is only sensitive to sexual sensation, it may cause the geese to have only an urgent situation, which affects the quality of life of the goose or abnormal behavior.

Machine vision and image processing have many applications in agriculture and industry. In the current situation of insufficient agricultural manpower, if the relevant technology can be applied to animal husbandry management, the cost and manpower effect can be reduced. At present, Taiwanese poultry farms have gradually begun to introduce photographic equipment to assist in feeding. Managers can monitor the internal conditions of the poultry house indoors, which not only reduces labor costs, but also reduces the frequency of managers entering the poultry house on site, reducing the chances of bringing geese to raise poultry and accidentally bringing into the pathogen.

At present, most of the cases in which imaging equipment is used to assist livestock production management must rely on manual observation of the picture to find abnormal conditions, and it is impossible to achieve automatic monitoring. Machine learning development technology, due to the powerful ability of the Convolutional Neural Network (CNN) to solve object detection problems, in recent years there have been attempts to use CNN in agriculture.

The purpose of this study was to develop a goose positioning and body temperature monitoring system. At the same time, the camera and the thermal imager are used to automatically take images of the goose life on the poultry house, and the Faster R-CNN with good accuracy in object detection is used to find out the position of the goose in the image. By comparing the image sequence to locate the location of the goose, the thermal image is integrated with the photo of the goose, and the temperature information of the goose in the image is recorded.

This system can be expected to monitor the health of the goose in the poultry breeding site, while at the same time achieving functions such as reducing costs, reducing human disturbance, and improving the safety of the goose. It is hoped that this study will be applied to the early warning system for avian diseases in the future by monitoring the body temperature of the goose and reducing the impact of the disease on the birds in the poultry farm.

This study expects to achieve the following goals:

(1) Develop a system that automatically captures images of the life of the goose.

(2) Develop a system that can find the location of the goose image.

(3) Develop a system that can determine the body temperature of the goose.

II. THE PAPERS EXCEPTRD TO READ

A. Study on Goose Image Recognition Using Convolutional Neural Networks [1]

Goose is one of the important poultry. In recent years, the emergence of "non-open" geese has raised the awareness of epidemic prevention of geese, and the analysis of goose behavior has become more important. However, the traditional manual observation method has the disadvantages of not being objective and having large errors, so a new analysis method is needed to solve this problem. In this study, we use the convolutional neural network and machine learning related methods to establish a goose image recognition system, predict the position of the goose in the image, and lay the foundation for using the image to analyze the behavior of the goose. The experimental object of the study was White Roman Goose, and the convolutional neural network related algorithm used was Faster R-CNN. The image recognition model predicted results with an average accuracy of 0.89, an accuracy of 81%, and a recall rate of 82%. In the future, it is expected to develop a new goose behavior recognition model based on this research, and gradually replace the traditional method of using manpower.

B. Analysis of Goose Non-Moving Pattern Using Convolutional Neural Networks [2]

With the awareness of bio-safety and the development of the scale, poultry owners begin to avoid contact between poultry and wild birds and improve automation. In recent years, the development of machine learning has expanded the application range of Convolutional Neural Networks in various fields. This work will analyze the non-moving pattern of goose in wet-pad poultry houses. In the study, a raspberry-pi and two cameras were used to capture goose images with a five-second interval and upload it to the Network Attached Storage. The Position Detection System uses Faster R-CNN to create a model for finding the location of the goose in the image. The Dwell Time Calculation System uses the goose position obtained by the Position Detection System to calculate the overlap rate of individual goose at different times and calculate the dwell time. The Goose Dwell Pattern Analysis System developed in this study, in which the goose position detection model can achieve more than 90% both precision and recall. After analyzing the data for 14 days, we found that the relationship between the dwell time and the occurrence frequency follows the power law. It is recommended to be able to integrate other information, such as temperature and humidity or distance between geese, for correlation analysis, and hope to use this research as a basis to achieve the goal of warning in the future.

C. Monitoring chicken heat stress using deep convolutional neural networks [3]

Poultry and eggs are one of the major sources of protein in our diet, not only the high nutritional value, but also the main raw material of many processed foods. In the past decade, an average of about 550000 metric tons of chicken have produced per year in Taiwan, accounting for 31.19% of total volume of animal husbandry sales. As a result, chicken production is an importance economic value in animal husbandry. However, high ambient temperatures in tropical and subtropical areas result in the heat stress in chickens, further leading to economic loss and reduced welfare in the chicken industry. The detrimental effect of heat stress reduces growth rate of broilers and egg quality, even associated with sudden and massive deaths. Early detection on heat stress is a key to stabilize poultry and egg production. Therefore, a method to monitor heat stress on chicken in real time is necessary.

Conventionally, chicken heat stress is evaluated by temperature-humidity index (THI). In general, a THI value of 21 is considered as the threshold for chicken heat stress. THI is, however, an indirect indicator. With the development of computer vision, image-based approaches have been increasingly applied for monitoring poultry behavior because of the advances in digital photography and image processing. The study, a raspberry-pi V3 and a web camera were used to acquire images of broilers at a rate of 1 fps.

In recent years, deep learning was emerged as a powerful tool for objects detection and recognition problems in images. This study proposed to track chicken movement using deep learning approaches. Convolutional neural network classifiers were developed to identify and localize the broilers in the images. The combination of chicken activity and THI values can be used as a new predicting indicator to avoid the phenomenon of chicken heat stress.

The specific objectives of the study were to (1) build a low cost embedded system to acquire images and environmental factors from a chicken coop, (2) build a model to detect and localize chickens in the coop using Faster R-CNN, (3) track chicken movements, and (4) find the correlation between chicken movement and THI values.

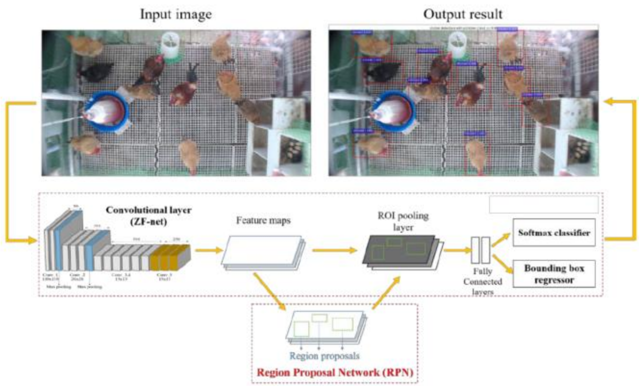

Fig. 1. The architecture of Faster R-CNN model.

D. Broiler stunned state detection based on an improved fast region-based convolutional neural network algorithm [4]

Electric stunning is an important aspect of poultry slaughtering and processing. Moderate stunning can render broilers unconsciousness for between 40 and 52 s. This condition provides the best bloodletting rate, easier feather removal, and minimal carcass damage, and the meat is more tender. However, when insufficiently stunned (i.e., the electrical current reaching the brain is too low), broilers still sensitive to pain and stress, clonic-tonic convulsions (death struggle) will occur, leading to carcass damage (broken wings and clavicles). Excessive stunning can also result in quality defects, such as clavicle rupture, bleeding from arteries and capillaries, and a large number of needle-like blood spots near the top of the chest. Therefore, moderate stunning plays an important role in ensuring the quality of chicken meat.

The amount of current, the electrical frequency, the electrical waveform, and the stunning time are the most common parameters that can be optimized to improve the stunning effectiveness. Exactly the same electric stunning conditions can have widely divergent effects on broilers, depending on their breed, age, and body weight. To obtain an optimal stunning effect, the frequency and voltage of the electric stunning machine has to be adjusted in real time, according to the condition of the broiler and its stunned state after checking. However, due to individual differences, the moderate stunning of broilers is not currently verified in many small and medium broiler processing plants. Most broiler slaughtering companies do not apply objective criteria or online detection methods and techniques to ensure that broilers are moderately stunned. Workers preset the stun voltage and frequency, according to their experience, and these settings then remain fixed and are not adjusted according to the breed, weight, age, or stunned condition of the broiler being slaughtered. This results in a significant number of insufficiently or excessively stunned broilers being slaughtered in broiler slaughterhouses.

Previous studies conducted found that, after moderate stunning, chickens hold their wings in close contact with their bodies and their necks are arched and stiff. When they are improperly stunned, their appearance is significantly different. These characteristics make it possible to clearly discriminate whether a broiler is in an appropriate stunned condition.

To overcome the existing problems and variable quality in the chicken industry, the frequency and voltage of electric stunning needs to be properly adjusted by correctly detecting and identifying the stunned state of each individual broiler. Currently, the stunned state of shocked broilers is usually left to manual vision detection. This is not only time-consuming, inconvenient, and subjective, but it does not allow for a rapid adjustment of voltage and frequency. Over the past 2 decades, machine vision and image processing technology has developed rapidly and it has begun to be used more and more frequently in agriculture for the detection and identification of a range of phenomena. A new technology has been developed that uses modified pressure and imaging to detect microcracks in eggs. Research has shown that the system to have an accuracy of 99.6% in detecting both cracked and intact eggs. In relation to broilers, a line-scan machine vision system and multispectral inspection algorithm were developed and evaluated for differentiation of wholesome and systemically diseased chickens on a high-speed processing line, which correctly identified 97.1% of systemically diseased chickens.

The image recognition accuracy largely depends on the extraction and feature selection. To accurately determine and identify the stunned state of a broiler, it is necessary to accurately extract the features of its stunned state and to then select the features that are meaningful. In recent years, deep learning has produced outstanding results in the field of image recognition. Amongst a range of possible approaches, convolutional neural networks (CNN) are particularly effective at automatically extracting the appropriate features from a training dataset without the need for manual feature extraction. Although the training period is long, it takes less time to test this approach than other methods based on machine learning, and it is widely recognized to be one of the best approaches to image recognition.

When using machine vision technology to identify the stunned state of broilers, the recognition target is a unitary broiler and the features to be identified remain largely the same. In this paper, authors propose using a multi-layer residual module (MRM) to obtain detailed feature extraction. Based on this, authors have developed an improved and optimized fast region-based convolutional neural network (Faster-RCNN+MRMnet) model that can precisely identify the stunned state of broilers. Development of the model has involved the creation of training image datasets containing 3 types of stunned condition: insufficiently stunned, moderately stunned, and excessively stunned.

E. *Analysis of Dogs' Sleep Patterns Using Convolutional Neural Networks* [5]

Video-based analysis is one of the most important tools of animal behavior and animal welfare scientists. For instance, it is very useful for measuring time budget of animals, a common ethological and welfare parameter, indicating the amount or proportion of time that animals spend in different behaviors. In this case the data to be analyzed may amount of hundreds of hours of data, and is a tedious and error-prone task. Naturally, automatic video analysis has the potential to revolutionize the work of animal scientists in terms of precision, nature and number of behavioral variables that can be measured, and volumes of video data that can be processed. Automatic video-based systems already exist for different species: wild animals, pigs, poultry, insects, and many more. Moreover, well-developed commercial systems for rodent tracking are widely used in behavioral research.

Dogs are a widely studied species in animal science. While video analysis is widely applied in the context of dogs, very few works address automatic video-based analysis of dog behavior. All of these works use video from 3D Kinect camera, the installation and use of which is not trivial and also quite expensive.

In this paper authors present a system developed for supporting an ongoing research project in animal science, investigating sleeping patterns of kennelled dogs as indicators of their welfare. The system was developed for automatically quantifying dogs' sleeping patterns. It combines convolutional neural networks with classical data processing methods; it works with very low quality video data, and supports detecting multiple dogs in a frame. In what follows authors describe in further details the research problem and the developed solution.

F. *Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks* [6]

Object recognition has been a driving motivation for research in computer vision for many years. Recent progress in the field has allowed recognition to scale up from a few object instances in controlled setups towards hundreds of object categories in arbitrary environments. Much of this progress has been enabled by the development of robust image descriptors. Another enabling factor has been the development of increasingly large and realistic image datasets providing object annotation for training and testing.

Neural net-works have a long history in visual recognition. Inspired by the neural connectivity pattern discovered by Hubel and Wiesel, Fukushima's Neocognitron extended earlier networks with invariance to image translations. Combining the backpropagation algorithm with the Neocognitron architecture, convolutional neural networks quickly achieved excellent results in optical character recognition leading to large-scale industrial applications.

Convolutional neural networks (CNN) are high-capacity classifiers with very large numbers of parameters that must be learned from training examples. While CNNs have been advocated beyond character recognition for other vision tasks including generic object recognition, their performance was limited by the relatively small sizes of standard object recognition datasets.

Notably, many successful image classification pipelines share aspects of the Neocognitron and convolutional neural networks. Quantizing and spatially aggregating local descriptors arguably produces low-level image features comparable to those computed by the first two layers of the Neocognitron. It is therefore possible that these manually designed pipelines only outperformed earlier CNNs because CNNs are hard to train using small datasets.

This situation has changed with the appearance of the large-scale ImageNet dataset and the rise of GPU computing. Convolutional neural networks (CNN) have recently shown outstanding image classification performance in the largescale visual recognition challenge (ILSVRC2012). The success of CNNs is attributed to their ability to learn rich midlevel image representations as opposed to hand-designed low-level features used in other image classification methods. Learning CNNs, however, amounts to estimating millions of parameters and requires a very large number of annotated image samples. This property currently prevents application of CNNs to problems with limited training data. Given the "data-hungry" nature of CNNs and the difficulty of collecting large-scale image datasets, the applicability of CNNs to tasks with limited amount of training data appears as an important open problem.

To address this problem, authors propose to transfer image representations learned with CNNs on large datasets to other visual recognition tasks with limited training data. In particular, authors design a method that uses ImageNet-trained layers of CNN to compute efficient mid-level image representation for images in Pascal VOC. Authors analyze the transfer performance and show significant improvements on the Pascal VOC object and action classification tasks, outperforming the state of the art. Authors also show promising results for object and action localization. Results of object recognition and localization by this method are illustrated in Figure 2.

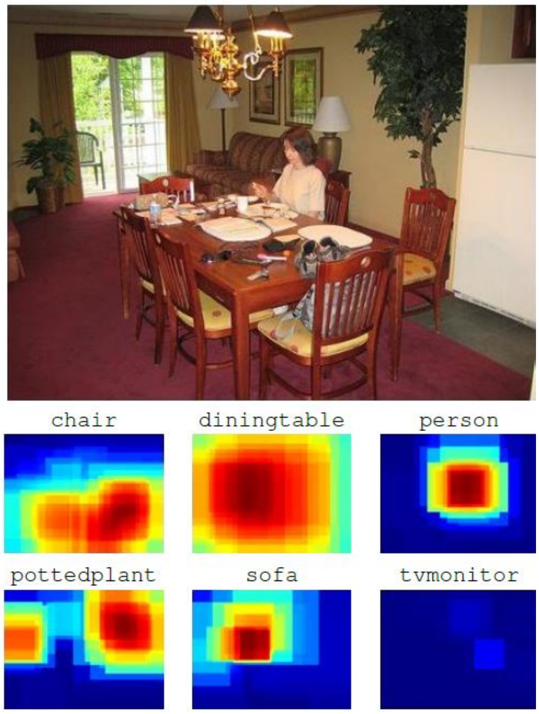

Fig. 2. Recognition and localization results of our method for a Pascal VOC test image. Output maps are shown for six object categories with the highest responses.

G. *A Convolutional Neural Network Cascade for Face Detection* [7]

Face detection is a well studied problem in computer vision. Modern face detectors can easily detect near frontal faces. Recent research in this area focuses more on the uncontrolled face detection problem, where a number of factors such as pose changes, exaggerated expressions and extreme illuminations can lead to large visual variations in face appearance, and can severely degrade the robustness of the face detector.

The difficulties in face detection mainly come from two aspects: 1) the large visual variations of human faces in the cluttered backgrounds; 2) the large search space of possible face positions and face sizes. The former one requires the face detector to accurately address a binary classification problem while the latter one further imposes a time efficiency requirement.

To achieve fast face detection, authors present a CNN cascade, which rejects false detections quickly in the early, lowresolution stages and carefully verify the detections in the later, high-resolution stages. They show that this intuitive solution can outperform the state-of-the-art methods in face detection. For typical VGA size images, the detector runs in 14 FPS on single CPU core and 100 FPS on a GPU card.

In this work, authors contributions are four-fold:

(1) We propose a CNN cascade for fast face detection.

(2) We introduce a CNN-based face bounding box calibration step in the cascade to help accelerate the CNN cascade and obtain high quality localization.

(3) We present a multi-resolution CNN architecture that can be more discriminative than the single resolution CNN with only a fractional overhead.

(4) We further improve the state-of-the-art performance on the Face Detection Data Set and Benchmark (FDDB).

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