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Development of an early warning algorithm to detect sick broilers

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ABSTRACT

The frequent occurrence of poultry diseases, such as bird flu, not only causes huge economic losses to farmers but also seriously threatens the health of human beings. Providing early warnings of new poultry disease outbreaks is essential in poultry breeding. With the rise of digital image processing technology and machine learning algorithms, real-time monitoring of poultry health status through cameras is an effective way to prevent large-scale outbreaks of disease. To analyze the postures of healthy and sick broilers, bird flu virus was inoculated intranasally into healthy broilers manually. The broilers were then placed in isolator cages for comparative experiments. The methods of observing the posture changes of broilers and extracting the key features are used to realize the automatic classification of healthy and sick broilers. In this research, broiler images are obtained, and two kinds of segmentation algorithms are proposed to separate the broilers from the background to obtain the outlines and skeleton information of the broilers. According to the preset feature extraction algorithm, the posture features of healthy and sick chickens are extracted, the eigenvectors are established, the postures of the broilers are analyzed by machine learning algorithms, and the diseased broilers are predicted. A series of experiments have been done. Data for each feature acquired by the algorithms are analyzed, and the effect of each feature on the recognition accuracy is obtained. Using some of the features proposed in this research, accuracy rates of 84.248%, 60.531% and 91.504% are obtained, but using all the features can yield an accuracy rate of 99.469%. Then, the recognition effects of several commonly used machine learning algorithms are compared. The Support Vector Machine (SVM) model obtains an accuracy rate of 99.469% on the test samples, which is superior to those of the other machine learning algorithms. The experimental results show that the algorithms proposed in this research can effectively separate broilers from the background, extract the posture information of broilers, and accurately and quickly identify the health status of broilers by means of SVM. The algorithms for digital image processing and machine learning are evaluated in the diagnosis of broiler health status and show high accuracy, good stability and good generalization performance, and can give early warning signals. This research can provide a reference for the intelligent identification of broiler health status in the future.

1. Introduction

In recent years, the frequent occurrence of poultry diseases has seriously impacted poultry farming. Poultry diseases not only cause huge economic losses to farmers but also seriously threaten the health of human beings. Therefore, poultry diseases have become key issues of concern to poultry breeders and governments. At present, the primary diagnosis of poultry disease mainly depends on the observation of gestures, cockscombs, feces and sounds by veterinarians (Mollah et al., 2010; Aydin and Berckmans, 2016). Manual observation (Mortensen et al., 2016) is time-consuming and laborious and can even fail to detect the diseases. Therefore, researchers aim to use digital image processing technology to observe poultry diseases by using cameras and computers to obtain digital images of poultry.

Several studies have focused on ways to detect the behaviors of broiler breeders; for example, Aydin et al. (2010) developed a fully automatic monitoring technique to measure broilers' activities using different gait score levels. Two experiments were carried out to assess gait scores obtained by human experts and the image processing system. They analyzed different gait score groups to identify the broiler behaviors. Kristensen and Cornou (2011) applied a model that can automatically record broiler chicken activities. In their research, they described the undisturbed levels of activity of chickens over three weeks. A method was applied to detect deviations of broiler activity from the specified level at a given age for to notify the producer in a timely manner. Pereira et al. (2013) presented a method that used

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image processing technology to recognize the behaviors of broiler breeders. A sequence of frames was captured to determine a correspondence between body shapes and the behaviors expressed by the birds. First, each behavior was determined. Second, different behaviors were classified. Third, an image processing algorithm was used to separate the birds from the background. At last, a behavioral classification tree was constructed. For this stage, the "set training" mode had an overall rate of success of 96.7%, and the "cross-validation" mode achieved a 70.3% success rate. Youssef et al. (2015) examined the possibility of controlling chickens' activity levels and positions in a small chamber via controlling the surrounding micro-environment. In their study, 30 sensors were placed to record the temperatures. A digital CCD camera was set on the top of the chamber to capture the chickens' motions and positions. They defined real-time models to describe the dynamic responses of the chickens' activity to the changes in the temperature. Abdanan Mehdizadeh et al. (2015) presented a machine vision technique that visually identified the relevant biomechanical variables attributed to broiler feeding behavior by using high-speed video footage. Three five-day-old broiler chicks were manually measured and these measurements were compared to the automatic measurements. The position of the eye center was calculated automatically to determine the position of each bird's head. Otsu's threshold was applied to the image to detect the beak tips. Then, the distance between the upper and lower beak tips could be calculated at a high level of accuracy, with an error of less than 1.05 mm. Mortensen et al. (2016) used Kinect to predict the weight of broiler chickens. First, a range-based watershed algorithm was used to segment the images. Then, twelve different weight descriptors were extracted. At last, individual broiler weight was predicted by the method of Bayesian Artificial Neural Network, and four other models for weight prediction were also evaluated. The system can predict broiler weight without using a weighing apparatus. It can also predict which birds are ill.

This research aims to develop a methodology to analyze the posture of healthy and sick broilers and to realize their automatic classification.

2. Materials and methods

Four to six weeks old chickens were housed in isolator cages and divided into two groups. Ten chickens of the R381 group were inoculated intranasally with 106 EID50 of H5N2 avian influenza viruses (R381/2008) in a 0.1 ml volume. Ten chickens were inoculated intranasally with 0.1 ml phosphate buffered saline (PBS) as a control group. All chickens were observed for clinical symptoms for 14 days.

The algorithm was based on VS2013 and OpenCV 2.4.13. A Logitech C922 CCD camera was used. Images were captured with a resolution of 640 by 480 pixels (see Fig. 1). The camera was attached by a USB port to a computer with a quad-core processor with 3.20 GHz per core, 4 GB of memory and Windows 7 installed (Shi et al., 2016). Standard C/C++ language was used to program.

First, the algorithm extracts the poultry target from a complex background. Then, the skeleton structure of the poultry can be calculated. The eigenvectors are established according to the features in the dashed box in Fig. 2. The algorithm analyzes whether the poultry is in a pecking state. Finally, the health status of the poultry is evaluated by the Support Vector Machine (SVM) (Matuska et al., 2014; Morales et al., 2016).

2.1. Poultry segmentation algorithm

The accurate separation of poultry from a background image is the first problem in the visual diagnosis of poultry disease (Sergeant et al., 1998). To this end, the following poultry segmentation algorithms are presented.

2.1.1. Ellipse model

The real-time poultry segmentation algorithm based on the ellipse

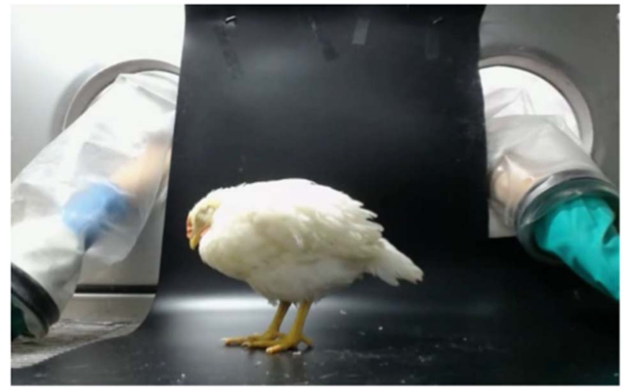

Fig. 1. Shooting environment. Ethics statement: All experiments were carried out in ABSL-3 facilities, in compliance with and using protocols approved by the biosafety committee of South China Agriculture University. The handling of chickens and mice was performed in accordance with the guidelines approved by the experimental animal administration and ethics committee of South China Agriculture University.

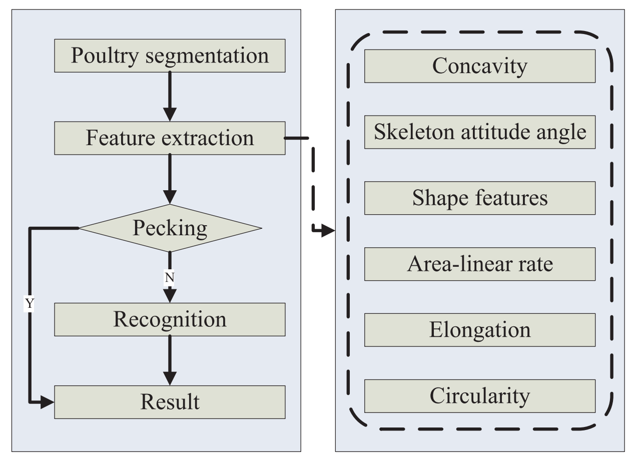

Fig. 2. Algorithm flow chart.

model (Kashiha et al., 2013, 2014a, 2014b) uses the existing poultry color feature template to approximate the target so that it can divide the poultry target from the background in a new frame. To select a better color space, the HSV (Hue, Saturation, Value) and the Lab (CIE L ∗ a ∗ b) color spaces are used to extract the color features of the poultry in the template, as shown in Fig. 3.

In Fig. 3(b) and (c), *S* and *V* are widely distributed and divergent, which is not conducive to the selection of the target. Although *H* is clearly visible, the segmentation accuracy obtained using only *H* is not high enough, and it is too difficult to extract different saturations or values at the same time. In Fig. 3(d) and (e), *a* and *b* are clearly visible and clustered. Therefore, the *a-b* map can be used to describe the poultry color features and the *L-a* map can be used for auxiliary description.

In this method, an ellipse is used to fit the poultry features in the *a-b* map, and the parameters of the ellipse are recorded. Then, the range of *L* in the *L-a* map is extracted. After that, the color features of the poultry are obtained. The poultry color features are described using an elliptical column in three dimensions. Then, each pixel is judged in every new frame image: the pixels for which the Lab color features are in the elliptical column are preserved; other pixels are deleted. The maximum contour that consists of reserved pixels is selected.

After separating the chickens from the background, the elliptical column is reestimated. To prevent drifting, 70% of the elliptical column information is the same as in the original template, and only 30% is updated information. Under this standard, adjusting the size and orientation of the ellipse can make the algorithm well adaptable to