**Bulletin of Environment, Pharmacology and Life Sciences**
Bull. Env. Pharmacol. Life Sci., Vol 3 [8] July 2014: 05-11

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD
Global Impact Factor 0.533
Universal Impact Factor 0.9804

**ORIGINAL ARTICLE**

# Early Determination of Pharaoh Quail Sex after Hatching Using Machine Vision

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**ABSTRACT**
*This study examines machine vision and pattern recognition algorithms which interrogate ventral neck area color and textural characteristics to automatically and non-destructively detect Pharaoh Quail sex. A total of 28 birds (14 males and 14 females) were dissected from one day of age. Thirty seven color and texture features were extracted from ventral neck area. Six features were selected based on t-Test and Receiver Operating Characteristic (ROC) analysis. These six features were utilized to predict quail sex using Support Vector Machine (SVM). The proposed automatic computer vision system differentiated males and females with 100% and 92% accuracy, respectively. This investigation showed the promising potential of texture and color analysis, in combination with image analysis, for the non-destructive prediction of quail sex.*
***Key words:*** *Pharaoh Quail, sex determination, machine vision*

**Received 23.03.2014** **Revised 15.04.2014** **Accepted 01.06. 2014**

## INTRODUCTION

Japanese quail (*Coturnix Japonica*) were domesticated in Japan around the 11th century as a pet song-bird [1-3]. After being gradually introduced to other Asian countries, the bird was brought to the USA and Europein the period 1930-1950, where it become widely used for meat and egg production [4-5].Based on plumage color, six strains of Japanese quail are registered. The Pharaoh Quail strain is recommended for meat production because they have greater body weight compared to other quail breeds and varieties [6-8].

Usually, separation of male and female Pharaoh Quails begins after 14 days of age when clear sexual dimorphism begins to show according to the color of the plumage. Differentiation of quail gender is finalized 17-20 days of age when the birds show clear sexual dimorphism in plumage color [9].

The early and accurate sexing of Japanese quails presently creates serious problems in South-East and East Asian countries where the producers have directed their efforts mainly towards egg production. Previous optical methods are extremely labor intensive and difficult to use [10]. Optical methods are restricted by the small size of newly hatched quails vents compared to the size of the optical tips used. Moreover, the high expenses of the sexoscopes and the optical tips combined with increased mortality rates due to the resulting injury of their use are impediments to the application of optical methods [11].The expenses incurred before sexing at the age of 17-20 days are very high;30 to 100% of expenses related to the rearing are spent in this period, which makes early elimination of the surplus males appropriate [9]. Therefore, an automated process to correctly identify Japanese quail sex is critical to achieve economic egg production.

Computer vision and pattern recognition technology has rapidly developed in many agricultural fields e.g. quality evaluation, fault and disease diagnosis in agricultural products [12-16] and understanding chicken behavior [17-18]. It also has been used in determination of the sex of Pacific oysters [19] and sex detection of individuals of *Ceratitis capitata* [20].

There is little published information available on the use of computer vision in the automation of the sex determination of avian species. Pharaoh Quails exhibits an apparent sexual dimorphism in plumage color that could be used in the earliest possible determination of their sex. Thus, this study aims to develop computer vision techniques to capture images to analyze the sexual dimorphism of living Pharaoh Quails for the sex determination one day after hatching.

## MATERIAL AND METHOD

The feathers of adult female Pharaoh Quails are speckled with dark colored spots. Adult male Pharaoh Quails have dark rusted feathers on the breast and neck. In this study, male and female identification was made using machine vision based on the thickness and uniformity of the black feathers on the ventral neck area. In female chicks, this area is denser and a homogenous black color but in males it is characterized with diffuse white color which appears to be brighter.

### Image acquisition system

At hatching, 28 one-day old chicks were selected randomly. Images were taken in a binocular microscope (Olympus, Japan) capable of acquiring images with a maximum size of 640 × 480 pixels. The scene was backlit using a fluorescent tube to obtain good image contrast, which enhances the classification capabilities of color and texture parameters. The microscope was equipped with a camera under 100 × magnifications.

Chicks could randomly change their position and orientation from one image to the next due to the operator hand's position and orientation. Thus, five images were taken of each sample to minimize the number of classification errors due to the position and orientation of the chicks. Fig. 1 shows the ventral neck area of female (A) and male (B) chicks to exemplify their color and textural differences.

A

B

Fig. 1: ventral neck area of female (A) and male (B) bird

The chicks were then euthanized by exposure to a rising concentration of carbon dioxide ($CO_2$) [21]. The abdominal cavity was opened and the gonads (ovary/testicles)(Fig. 2) were examined to accurately reveal the sex of the chick. This revealed a total of 14 male and 14 female birds, which was used to classify the 140 corresponding pictures into two different classes, i.e. 70 males and 70 females.

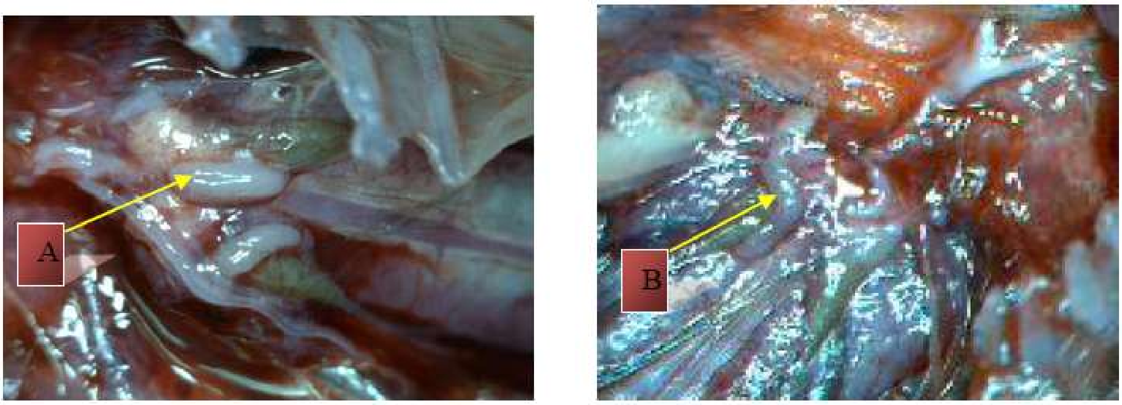


Fig. 2: Reproductive organs 1-day old pharaoh quails. A. In left- testicle, B. in right- ovary

**Algorithm for detecting the sex**

An algorithm consisting of feature extraction, feature selection and pattern recognition was designed to sort quails into male and female groups. The data analysis algorithm is shown in Fig. 3. The image analysis was performed using Matlab® software (MathWorks, Inc., Natick, Massachusetts, USA).

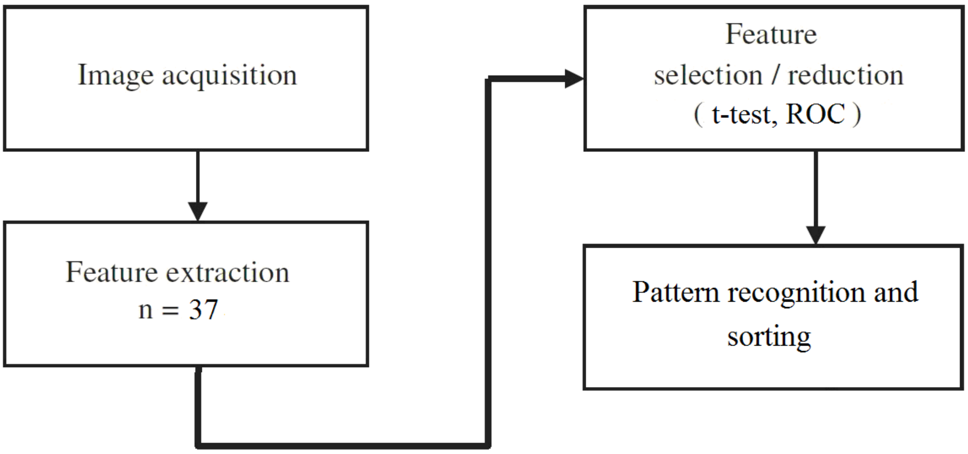


Fig. 3.The algorithm of data analysis.

**Feature extraction**

Having an accurate sorting system relies on the features extracted from the image. Therefore, feature extraction plays an important role in developing this sorting system. In this study, all of the acquired images were manually segmented into ventral neck area and background. Then, color and texture features were extracted from the segmented ventral neck area images.

Using Andreasen et al. [22] red, green and blue (rgb) color characteristics (g=256*(G/(R+G+B)), (b=256*(B/(R+G+B)) and (r=256*(R/(R+G+B))) were extracted.

The images were converted to a binary format (1 and 0 values). The binary value – the summation of the 1values- highlighted substantial differences due to the color differences evident between males and females (Fig 4).

 

**A**

**B**

Fig. 4: binary image of ventral neck area of female (A) and male (B) bird

After extracting these two features, the original images were converted to gray scale images. Six separate textural features were extracted from the GLCM [23-24], eleven from GLRLM [25-26], four from GLDM [27], five from NGTDM [28] as well as seven statistical features [29-30]. A total of 37 features were thus taken into account in distinguishing between the two sexes.

**Feature selection**

A subset of the 37 extracted features has to be chosen since irrelevant/redundant features add noise to the system and degrade its performance [31]. Using all available features is also computationally unreasonable. Therefore, each feature was statistically analyzed using the t-Test [32] to check if the mean values of the two classes differ significantly or not. If not, the feature was discarded. Next, a Receiver Operating Characteristic (ROC) curve [33] curve, which is a measure of the class discriminatory capability of a certain feature, was plotted for the remaining features. Accordingly, a total of six features were identified as the most effective features and were used in the remainder of the study. These features were: binary value; g form color; and coarseness and strength from NGTDM and HGRE and SRE from GLDM.

**Pattern recognition and sorting**

It is necessary to have a system that has the ability to identify quail sex with high accuracy. Therefore, Support Vector Machines (SVM), which is a supervised learning algorithm, was chosen for sex determination. First, data nonlinearly maps to a high-dimensional feature space by kernels and then tries to find the hyperplane that separates data with maximum margin in that new space [34]. This classifier gives better results for sorting problems compared to other classifiers [35]. The commonly used kernels are the Radial Basis Function (RBF) kernel, the Sigmoid Kernel and the Polynomial Kernels [36]. Nashat et al. [37] used polynomial and RBF classifiers in SVM for real-time inspection of biscuits on moving conveyor belt and found the RBF kernel to be more accurate than the polynomial kernel. Therefore, in this study the RBF kernel was utilized.

The next step was training and testing the sorting system. The system was trained using two-third portion of the data set (45 images from each gender group) and was based on the six selected features as identified above. The RBF kernel parameters were globally optimized with a grid search and leave-one-out cross-validation method [38]. When the optimum SVM model was built, the generalization ability of the model was determined using the test data set (the remaining 25 images from each gender group).

**Expert person evaluation**

To evaluate the computer vision system, pictures were shown to an expert person. Then, statistical evaluation using chi-squared test was carried out (the level of significance is set at $p<0.05$). The precise calculation of Chi-Square ( $\chi^2$ ) is given by Kaps and Lamberson, [39]:

$$\chi^2 = \sum \text{(Observed Frequency - Expected Frequency)}^2 / \text{Expected Frequency}$$

**Results and discussion**

As illustrated in Table 1, the results show that from the test data set, females were correctly detected in 23 from 25 images; viz. female birds were incorrectly identified as males in 8% of the test cases. Better results were obtained in the case of males, which were correctly in 100% of cases.

Table 1: SVM classification for female and male classes

| Class | No. of test Samples in each group | No. of correct classification | Accuracy (%) |
|---|---|---|---|
| **Female** | 25 | 23 | 92 |
| **Male** | 25 | 25 | 100 |

These results are consistent with the methodological tools developed by Costa et al. [40] for the on-line sorting of farmed seabass (Dicentrarchuslabrax, L.) for size, sex and the presence of abnormalities. They reported 95% and 54% correct classification for male and female, respectively. Furthermore, Blasco et al. [20] proposed and tested a machine vision system to automatically determine the sex of adult C. capitata (Mediterranean fruit fly). Their simulation tests with 1,000 flies (5,000 images) had 100% success in identifying male flies, with an error rate of 0.6% for female flies.

While females are most commonly are a denser, homogenous black color compared to the male, in some cases their plumage appears as a diffuse black color. This fact will explain the confusion of incorrectly identifying a female's images as a male. Because production efforts are mainly directed towards egg production, determining female sex is more important for famer than male, but unfortunately this algorithm is more precise for detecting male sex than female. However, due to the high cost of raising chicks in the first 14 days, the proposed computer vision method is promising due to the 92% and 100% accuracy for female and male differentiation, respectively.

Chi-square analysis of the results from sexing by an expert person shows no significant difference between the observed and expected frequencies for the sexes ( $\chi^2 = 0.2883$, $P = 0.5913$). Therefore, a visual inspection of the ventral neck area by an expert person cannot differentiate male and female sexes while the result proposed method strongly differentiates quail with high accuracy.

**CONCLUSION**

Dubiec and Zagalska-Neubauer [41] stated that in many bird species, males and females cannot be discriminated on the basis of external characteristics and proposed DNA-based techniques. These hybridization or polymerase chain reactions methods are time consuming and need certain skills, which is an impediment for use in the industry. However for quails, which are selectively bred, the ventral neck area, an external part of the bird, can be evaluated to accurately, efficiently and rapidly sort males from

females. Importantly, this optimizes the breeding scheme and makes significant economic gains because sorting can occur at one day of age rather than 17 – 20 days.
Results of this study show that this method is a reliable, efficient, non-destructive and high-precision technique to detect gender. Simultaneously, it establishes the necessarily theoretical and practical basis for further studies, and could be used for building an automatic sexing machine.

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**Citation of This Article**
Saman A M, Gary S, Amir G, Mohammd A K T. Early Determination of Pharaoh Quail Sex after Hatching Using Machine Vision. Bull. Env. Pharmacol. Life Sci., Vol 3 [8] July 2014: 05-11