Gender Determination of Chickens Using Voice and Wavelet Transform

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***Abstract*—An intelligent fowls sexing system was developed based on data mining methods to distinguish hen from cock hatchlings. The vocalization of one-day-old hatchlings were captured by a microphone and a sound card and convert in to time-frequency domain using discrete wavelet transform. During data-mining from signals of these three domains, 25 statistical features were extracted. The Improved Distance Evaluation (IDE) method was used to select the best features and also to reduce the classifier's input dimensions. Fowls sound signals were classified by Support Vector Machine (SVM) and Artificial Neural Network (ANN). The highest accuracy of the SVM and ANN at time-frequency domains was 90.74 and 87 percent, respectively. Results showed that the proposed system could successfully distinguish between Hen and Cock hatchlings. The results further suggested that using SVM was more efficient than ANN in gender determination of chickens.**

***Index Terms*— Gender Determination; Wavelet Transform; Data mining; Support vector machine, Artificial Neural Network.**

I. Introduction

In most bird species (including ornamental birds), males and females cannot be distinguished morphologically. This is especially important for poultry hatchery owners. Fowl sexing is essential from different aspects including development, poultry growth and research [1]. The apparent sex is determined based on a series of physical properties related to each sex. A number of factors can change bird-generated signals including diseases, weakness and species. Since it is possible to detect vocalization signal features, different types of analyses can be performed.

In a review study, which is done by Volodin et al. (2015), has been considered that sexing by voice represents a feasible alternative to classical sexing techniques. This study is based on the analysis of computer images of vocalization [2]. Beside of this, different research studies have been carried out on Biosystems based on artificial intelligence and data mining methods. Banakar et al (2016), Designed an intelligent device for diagnosing avian diseases based on chicken's sound. They could detect the Newcastle, Infectious Bronchitis and avian influenza based on signal processing methods and Dempster-Shafer evidence theory with accuracy of 91.15 % [3]. Acevedo et al., (2009) used SVM to identify and classify 3 birds and 9 frog species based on their vocalizations. They used decision trees and linear discriminant analysis (LDA) for further studies, where the SVM recorded 95% accuracy in classification. Accordingly, the decision tree and LDA classified 89% and 71% of the cases, respectively [4]. Huang et al. (2009) used both the k-nearest neighbors (KNN) algorithm and SVM to develop an automated frog detection using vocalization characteristics. In this study, spectral centroid, signal bandwidth and threshold-crossing rate were the inputs of both classifiers, and the SVM performed better with 90.30% accuracy. The KNN also classified 89% of the cases [5].

This study introduced an artificial intelligence by signal processing approach to fowls sexing based on their vocalizations.

II. Materials and Methods

The study experiments were carried out in the Agricultural School of Tarbiat Modares University, Tehran, on a group of male and female fowls to develop an intelligent fowl sexing system. One-day-old Ross 380 hatched in an incubator were first sexed based on appearance difference (including wing differences) and Cloacal examination, and were then divided into 2 groups of sixty. Every single Subject chicken was placed in separate box. Recordings were made after 5 minutes of being in the box by a microphone (Microphone diameter: 9.7×6.7 mm, Impedance: ≤2.2KΩ, Frequency response: 100 ~ 16 kHz and Sensitivity: -58 dB ± 3 dB) and a PC to minimize stress. After recording, the chicken's sound were separated –and- saved in the "wav" format using wavePad Sound Editor software version 5.98 were analyzed at three time, frequency and time-frequency domains in MATLAB 2015a. A total number of 360 vocalization signals were collected from 120 male and female samples. Since it was impossible to visually extract information from unprocessed signals, features were extracted from signals in the three domains. The IDE method was used to score and select the best features and also to reduce the classifier's input dimensionality.

Using good signal processing - and - analysis, can extract useful information from signals and therefore prepare them for classification [6]. Besides noise removal, transforming signal from time to frequency or time-frequency domain can help obtaining useful details since a requirement of signal processing is to providing a proper signal for the data-mining stage [7]. In this study, time-frequency domain was used.

FFT perform poorly when dealing with unstable signal with time-varying frequencies because time transparency is zero in FFT [8]. On the other hand, frequency-domain and time-domain analyses fail to deliver simultaneous information

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on a signal's time and frequency. Discrete Wavelet Transform (DWT) is a 2-dimensional signal analysis used for achieving simultaneous time and frequency transparencies and is a highly effective method in signal analysis. Unlike FFT, Wavelet Transform (WT) do not treat all frequency components of a signal similarly, however, its main objective is to present an accurate time-domain and inaccurate frequency-domain transparency for rapid variations, and an inaccurate time-domain and accurate frequency-domain transparency for slow variations. This important advantage of WT makes it suitable for status monitoring application [8]-[9].

Qualitative and quantitative aspects should be considered during feature selection. Selecting several feature functions can complicate the classifier, making it incapable of distinguishing between two groups of extracted features from two signal classes [10].

SVM is a robust classifier first introduced by Cortes and Vapnik in 1995 building on the Statistical Learning Theory [11]. The main idea is to separate classes using a hypothetical hyperplane [12]. Depending on the relationship between data of classes, the classifier type can be varied including the linear, quadratic and Gaussian radial basis function (RBF) classifiers [13].

ANN is one of the most common and widely-used artificial intelligent techniques in identification and classification of signals [9]. In this study, neural network pattern recognition (NNPR) was applied for detecting signals and classifying healthy and unhealthy chickens. For this purpose, the data were divided into three groups: the first category included 70% of data for network training, the second category included 15% for validation of the network, and the third category included 15% for testing the neural network in terms of detecting and classifying new data. A feed-forward neural network structure was defined with three layers of input, hidden, and output and tan-sigmoid activation function.

III. Results and Discussion

In the time-frequency domain, the wavelet decomposition of each vocalization signal resulted into 125 features. Twenty five features (F1(AP4)-F25(AP4)) were statistical parameters of the approximation coefficient; twenty five features (F1 (DE1)-F25(DE1)) were statistical parameters of the first-level detail coefficient; twenty five features (F1(DE2)-F25(DE2)) were statistical parameters of the second-level detail coefficient; twenty five features (F1(DE3)-F25(DE3)) were statistical parameters of the third-level detail coefficient; and twenty five features (F1 (DE4)-F25(DE4)) were statistical parameters of the fourth-level detail coefficient [10].

Each feature was scored based on the IDE method, and data with the highest scores (25 features) were adopted as the best features, which were entered as SVM and ANN inputs. This study had 2 data classes, 180 samples in each class, and 125 features in the time-frequency domain in first-order and level four Daubechies wavelet transform. Table 1 shows the feature scores extracted from wavelet coefficient at the fourth level. Table 2 shows the performance of SVM and ANN. Study data include 360 recordings of hen and cock vocalizations, 70% of which (252-vocalization signal samples) were selected in a completely random fashion for SVM training purposes. The rest (30% or 108 samples) were used for testing the SVM to determine its sexing accuracy. The best result of SVM was obtained by σ=1. σ is related to the hyper plane width. The larger σ, the more general hyper plane. The smaller σ, the more local hyper plane [14]. Feed-forward neural network structure was defined with three layers of input, hidden, and output and tan-sigmoid activation function. In the input layer, one neuron was selected per feature. Since 25 features were selected as the best feature for chicken’s sound, the number of neurons in the input layer was selected as 25. The output layer of neural network was formed with 2 neurons since chicken’s signals had two classes. Nevertheless, the most important layer in designing the neural network was the hidden layer (middle layer). There is no rule and basis for the number of hidden layers, and the best number of layer is selected by trial and error [9]. Accordingly, the optimal structure of ANN was formed that is 9.

Maximum ANN and SVM accuracy values were obtained 87 and 90.63 percent, respectively and could correctly recognize 6 cocks out of 54 and 4 hens out of 54 [15].

TABLE I: Time-Frequency domain features (F) and their scores (S)

F	S	F	S	F	S	F	S	F	S
F_{23}	1	F_{72}	0.53	F_{76}	0.30	F_{19}	0.24	F_{120}	0.16
F_{6}	0.99	F_{69}	0.53	F_{87}	0.30	F_{5}	0.24	F_{122}	0.16
F_{12}	0.98	F_{33}	0.53	F_{27}	0.30	F_{112}	0.24	F_{18}	0.16
F_{17}	0.92	F_{22}	0.53	F_{18}	0.29	F_{64}	0.23	F_{26}	0.16
F_{22}	0.92	F_{48}	0.41	F_{104}	0.29	F_{72}	0.23	F_{49}	0.15
F_{11}	0.89	F_{71}	0.41	F_{116}	0.29	F_{68}	0.23	F_{42}	0.15
F_{8}	0.89	F_{27}	0.40	F_{82}	0.29	F_{118}	0.23	F_{45}	0.13
F_{3}	0.89	F_{12}	0.39	F_{87}	0.29	F_{33}	0.21	F_{32}	0.13
F_{2}	0.89	F_{110}	0.39	F_{100}	0.28	F_{64}	0.21	F_{82}	0.12
F_{13}	0.82	F_{108}	0.39	F_{117}	0.28	F_{83}	0.21	F_{38}	0.12
F_{7}	0.79	F_{114}	0.38	F_{123}	0.28	F_{124}	0.21	F_{81}	0.12
F_{19}	0.74	F_{42}	0.35	F_{125}	0.28	F_{92}	0.20	F_{31}	0.12
F_{73}	0.71	F_{47}	0.35	F_{38}	0.28	F_{38}	0.20	F_{22}	0.12
F_{28}	0.70	F_{21}	0.35	F_{88}	0.28	F_{9}	0.19	F_{16}	0.12
F_{24}	0.63	F_{107}	0.35	F_{82}	0.25	F_{83}	0.19	F_{86}	0.10
F_{62}	0.60	F_{38}	0.34	F_{77}	0.25	F_{119}	0.18	F_{65}	0.10
F_{53}	0.57	F_{98}	0.32	F_{121}	0.25	F_{32}	0.18	F_{22}	0.09
F_{58}	0.55	F_{83}	0.32	F_{38}	0.25	F_{83}	0.18	F_{1}	0.09
F_{21}	0.55	F_{48}	0.30	F_{38}	0.25	F_{78}	0.18	F_{111}	0.08
F_{61}	0.54	F_{79}	0.30	F_{37}	0.25	F_{112}	0.17	F_{82}	0.08
F_{67}	0.53	F_{102}	0.30	F_{36}	0.24	F_{2}	0.16	F_{102}	0.08

TABLE II: THE PERFORMANCE OF SVM AND ANN

Classifier	Structure	SVM Classifier Accuracy (%)	
		Train	Test
ANN	25*9*2	100 %	87 %
SVM	σ = 1	100 %	90.63 %

IV. CONCLUSION

The study analyzed vocalizations generated by male and female hatchlings in a bid to develop an intelligent fowl sexing system. For this purpose, the chicken's Ross 380 was studied and their vocalization was analyzed in time-frequency domains. The study results showed that intelligent practices could be useful and efficient for vocalization-based bird sexing. In this study, SVM classifier has given better result than ANN.This method can be done for another avian order and a comprehensive sexing device can be designed.

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