Advancements in Bioacoustic Analysis for Livestock Health Monitoring

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Introduction

Domesticated fowl (Gallus gallus, Gallus gallus domesticus) belong to the Galliformes, an order of birds with their domestication history dating back to 10,000 years ago in Vietnam. Fowl have the largest population among domesticated animals in the world as they exceeded 60 billion in 2015 (USDA, 2015). Due to meat storage challenges, the main objective of raising fowls was for laying eggs before 1960, with their meat being a secondary product (Boryan, Yang, Mueller, & Craig, 2011). Gradually, farms began to grow broiler chickens, and today these farms account for supplying a major part of human food supplies globally. Given the ever-increasing need for industrial chicken products as well as their special importance for ensuring human food security, recent decades have seen a marked growth in this industry. Of course, small chicken farms are spread throughout the world, as highlighted by the FAO's emphasis on sustainable food security and socio-cultural habits in developing small rural poultry farms (Kryger, Thomsen, Whyte, & Dissing, 2010).

Today, developments in processing and storage industries have eliminated most concerns for timely supply of products for consumers (Hastings, 1909), which have been replaced by concerns about poultry health in small and large farms. The FAO defines food security as:

Food security exists when all people, at all times, have access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life".

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Poultry diseases threaten not only the safety of the food but also its sufficiency by reducing production incentives in the event of huge financial losses due to epidemics. Since chickens are a main supplier of food protein, respiratory diseases can be considered as a serious threat for food security in poultry farming (Farrell, 2015). To reduce this threat, it is necessary to enlist the help of experts in other potentially related fields to help producers and veterinarians in addition to the food security policymakers. Avian diseases are highly diverse and can be classified based on several parameters. A conventional classification includes these groups: infectious respiratory diseases, neoplastic diseases, avian adenovirus virus diseases, viral diseases, bacterial diseases, parasitic diseases, and nutritional deficiency diseases. Among them, those targeting the respiratory system (*e.g.* flu, infectious bronchitis, and Newcastle disease) can be classified as respiratory diseases, which are the main group threatening poultry flocks (Davison, Kaspers, Schat, & Kaiser, 2011).

High outbreak speed of respiratory diseases is due both to their airborne nature and the high bird density in poultry farms. Therefore, once affecting a portion of the flock, it will be difficult to prevent the rest of the flock from the pathogen if timely diagnosis of these diseases is not available. Fast diagnosis is the most effective way to reduce the mortality rate. Although some of these diseases, such as Newcastle, target other systems of the bird body such as the nervous system along with the respiratory system. Among the common clinical signs (nasal discharge, retarded growth, general diarrhea, paralysis, etc.),

coughing and sneezing are two of the most common signs in this group, and all respiratory diseases cause rales (abnormal breathing sounds) in birds (Manning, Chadd, & Baines, 2007).The respiratory disease group has damaging effects on the vocal tract of birds, particularly on trachea and syrinx, thus affecting both their breathing behavior and the produced sound. Fig 1 shows instances of such effects.

Figure1. Inflammation of lytrax caused by a respiratory disease -Cornell University Atlas of Avian Diseases (PIADC).

Currently, these symptoms are diagnosed by experts and veterinary technicians. Although primary diagnosis, laboratory methods, and techniques play a significant role in diagnosing the disease, these methods are counted as empirical sciences where accuracy and precision of the diagnosis mainly rely on the expertise and the experience of farm technicians.

Sound is mechanical vibrations transmitted through the air (or other elastic/non-elastic mediums) at a speed of approximately 330 meters per second and can be heard when reaching a person's or animal's ear.

Human voice generating mechanism has three different parts: the lungs, the vocal folds within the larynx, and the articulators. The lungs (the pump) produce adequate airflow and air pressure to vibrate vocal folds (this pressure is the energy source of the voice). The vocal folds (vocal cords) form a vibrating valve that chops up the airflow from the lungs into audible pulses that in turn creates the source of laryngeal sound. The muscles of the larynx adjust the tension and length of the vocal folds to _fine-tune' pitch and tone of the created sounds.

The sound-producing mechanism in birds resembles humans to some extent. The main parts of sound production mechanism in birds are lungs, bronchi, syrinx, trachea, larynx, mouth and beak. Airflow from lungs travels through the bronchi to the syrinx, which is the main source of sound and resembles human vocal cords in function, but it is very different in terms

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of form (King, 1989). Sound from syrinx is then modulated by vocal tract, which consists of the trachea, larynx, mouth and beak (Kahrs & Avanzini, 2001; Smyth & Smith, 2002). In figure 2, a schematic view of this mechanism is presented (―The Respiratory System of Chicken,‖ 2016). The dimensions and constituents of the system vary considerably among the different species, but its overall structure is rather uniform (Fagerlund, 2004).

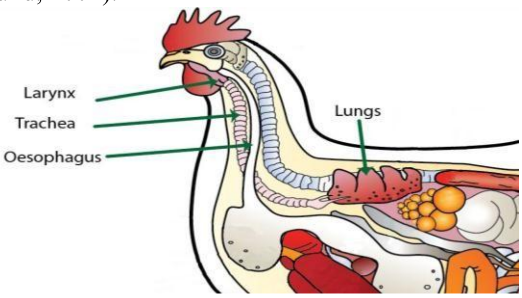

Figure2. A schematic diagram of the respiratory and vocal system components in chickens.

Emitted audio signals from animals contain information, and the auditory system is tasked with receiving and transmitting these to the brain. In recent years, authors have adopted audio sensors (microphones) and computer processors in a bid to simulate auditory and brain functions, and have attempted to extract and perceive messages in audio signals generated by both humans and other animals.

The objective of this study is to suggest an audio processing methodology for the early diagnosis of avian respiratory disease, with emphasis on the wavelet transform as the predominant tool. This method is inspired by the approach for diagnosing human respiratory diseases. As mentioned earlier, such diseases affect or even damage the respiratory system in different ways. Regarding the destructive effects of respiratory diseases on lungs (as energy source for the audio signals), trachea (as the sound conduit) and syrinx (as fundamental frequency generator), a correlation between audio signal features and the type and severity of avian diseases is predictable. The significance of this research follows from a number of factors including the position of poultry in the human food chain, its importance in food security, challenges posed by respiratory diseases threatening the poultry farms, and evidence of the avian diseases‘ effect on birds‘ sound signals. These factors point out that signal processing of chicken towards could help veterinarians and poultry farmers. In general, signal processing techniques have the following advantages: inexpensive, no training required, constant monitoring, inexhaustible, and human errors avoided.

Sound processing and its success

In several cases, signal processing systems have been proved to be highly accurate inexpensive systems with high repeatability. Examples of their satisfactory application in diagnosing disorders in biological systems are presented.

Many signal processing applications in biological systems have been focused on human voice, given its great importance. In studies on humans, the emphasis has been on systems for diagnosing vocal and respiratory diseases (Morillo, Moreno, Granero, & Jiménez, 2013), speech recognition (Pirhosseinloo & AlmasGanj, 2012), and speech synthesis (Reddy & Rao, 2016). Despite the orientation toward human applications, as well as perhaps due to the relative difficulty of working with animal vocal signals, there is a scarcity of scientific reports on animals. However there are still a small number of valuable reports in this field.

In 2010, a study entitled ―Cough sound description in relation to respiratory diseases in dairy calves‖ was carried out (S Ferrari et al., 2010). The authors studied three audio features of frequency, amplitude, and duration of dairy calves‘ sounds. Their main goal was to detect and distinguish cough from other normal sounds created in the surrounding environment, such as metal rack sounds. The research team found that the mentioned features are very useful in recognizing the coughs. In another study, a microphone array was used to diagnose pig coughs and locate their source as a sign of respiratory disease and the starting point of spread (Silva et al., 2008). Results showed that the system could successfully detect the sound source with a small error. In a study by Ferrari et al. (2008) cough sounds were used as the main indicators of respiratory diseases in pigs. It was revealed that audio features like the root mean square amplitude, peak frequency, and duration of cough sounds can be efficiently used to recognize the diseased and non-diseased sounds in pig houses. Aydin et al. (2014) adopted audio signal processing techniques to estimate the feed intake of broiler chickens.

In this research, an algorithm was developed to detect the individual pecking sounds of broiler chickens. The relationship between pecking sounds and the amount of feed intake was also investigated. The results of the algorithm were compared to reference feed intake values obtained through weighing scale measurements and video observations. The results also supported the high success rate of using such techniques in accurate determination of feed intake for broiler chickens. The research team extended their work in 2015 to successfully measure feed intake of broiler chickens with 86% accuracy (Aydin, Bahr, & Berckmans, 2015). Sound analysis techniques have been utilized to reduce the occurrence of chicken hatching in industrial incubators. This approach was based on frequency analysis of sounds recorded inside the incubator and aimed at identifying the time at which all the eggs reach the internal pipping stage (Exadaktylos, Silva, & Berckmans, 2011). The algorithm was able to pinpoint the time at which 93–98% of the eggs were in the internal pipping stage.

It could be said that the most related study in this area is what were done at the Georgia Institute of Technology (Carroll et al., 2014). Carroll et al. (2014) were successful in detecting rales in bird calls, which could potentially be good index of health condition in poultry flocks. This research is the most closely related study to the current study, as MFCC (Mel Frequency Cepstral Coefficients) was the primary processing tool used.

In many previous studies, perceptual features of the sound signals, decomposed in different cepstral or spectral frequency ranges, were applied as the main processing tool. In the light of formation mechanism of calls and the nature of their vocal signals, birds tend to call at a set of regular oscillations, which are resonated at integer multiples of harmonics of their fundamental frequencies. Considering the chicken respiratory system and its similarity to the human vocal system, the calls of birds challenged with respiratory disease would be distorted, and the severity of this distortion would depend on the severity of the disease‘s destructive effects on the vocal and respiratory

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tract. Thus, for more accurate detection of such distorted calls other than the routine perceptual sound features such as energy, shimmer, and jitter factors, and popular approaches such as cepstral and spectral analysis, processing techniques that potentially have more ability to detect distortion may be employed.

Wavelet transforms are typically mentioned as signal processing tools and are useful in detecting frequent patterns present in seemingly complex signals. Wavelet coefficients are the result of the inner product of scaled mother wavelets and target signals. This means that a wavelet transform reports the similarity of the object signal and scaled mother wavelet as a normalized number which is represented as a series of wavelet coefficients. Considering a bird call as input signal, and given that an appropriate wavelet family is selected, the wavelet transform can become a useful and powerful tool in detecting distorted bird calls.

Alternatively, wavelet transform has low sensitivity to noise and unwanted sounds, unlike other signal processing methods. This ability would be valuable in the processing of bioacoustics signals such as bird calls, especially when background sounds are present (e.g., ventilation systems, anthropogenic noises, etc.). All of these are due to the inherent filter-like operation of the wavelet transform.

Putting together the importance of poultry health monitoring, the signs of successful application of sound signal processing techniques for animal sounds, and the above mentioned capabilities of wavelet transform, this procedure might likely obtain valuable information about the birds' health condition and early signs of respiratory diseases. Not only are the side effect sounds detectable (e.g., coughs, rales, and sneezes), but also structural differences between the calls of healthy and unhealthy birds may be recognizable.

Proposed methodology

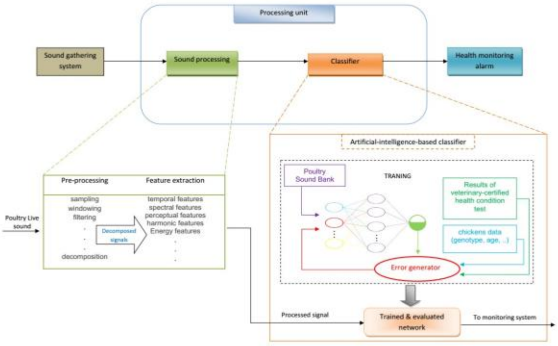

Figure 4. Schematic description of the idea for health monitoring.

This is a highly accessible target, and for this purpose a methodology is suggested which has three main steps. The first step includes developing a proper database from the recorded sounds produced by diseased and healthy target poultry; the second step is feature extraction from these signals; and the third step is to develop an algorithm to detect disease existence and severity.

A. Database

There is no doubt that avian sound patterns and features change during the growth period and probably during the entire lifespan. Since poultry sound databases are nonexistent, it is necessary to develop such a database for poultry at different ages to be used as a reference for representing different groups of normal and abnormal poultry sounds.

B. Data mining and feature extraction

Sound signals contain huge amounts of information, and it is virtually impossible to analyze in its entirety. Thus, audio signal features should be extracted and analyzed as representatives of the whole signal (figure 3). After selecting the appropriate wavelet family, and decomposition level, extraction of audio features is the most important step.

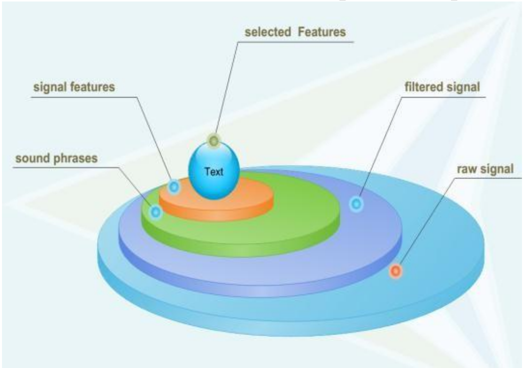

Figure 3. normal data reduction process in sound processing operation to reducing the data involved in a research.

Important acoustic information is usually in the form of quantities like frequency, spectral content, rhythm, formant location, etc. Features are typically divided into two categories: perceptual and physical. Perceptual features are introduced based on the way humans hear sound. Some examples of perceptual features are pitch, timbre and rhythm. On the other hand, the physical features are typically measured by evaluating statistical and mathematical properties of sound signals. Some examples of related physical features include: fundamental frequency (f0), zero-crossing rate (ZCR) and energy. Of course, a number of perceptual features are closely related to their physical dual as pitch is related to f0, while timbre is related to the spectral content (Gerhard, 2003). However, a full discussion about sound features and their extraction is out of the scope of this viewpoint article. For this purpose, the reader is referred to the literature in which interesting divisions of features can be found (Cotton & Ellis, 2011; Peeters, 2004; Wold, Blum, Keislar, & Wheaten, 1996).

The objective of the data-mining step is to extract audio signal features to be considered as accurately as possible.

Since there is no control over the direction and energy intensity of the sound source (birds), it is reasonable that the relative

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frequency-domain features can deliver more valuable indexes about the animal health status.

C. Classifier

In the pattern recognition field, many algorithms are introduced as classifiers which requiring considerable technical discussion for their review. What is important in this step, however, is to find those audio signal features that can be utilized to separate healthy signals from pathologic ones, and which could be efficiently distinguished. Artificial intelligence and machine learning algorithms can contribute to increase the resolution and reduce classification errors. The classifiers can then be trained, validated and tested using a healthy poultry sound database and veterinary-certified experimental test results.

The concept of this idea is presented in Figure 4.

There are some challenges in this regard, the most important of which are as follows:

- Separation of bird sound from other sounds such as ventilation system, pecking of food and water containers, flapping of wings, etc.
- Possible sound differences between various genotypes. In this case, different databases are required for different genotypes.
- Differences between female and male chicks; this problem arises particularly in broiler farms in where sexing in not usually performed.
- Differences in accuracy of signals captured by various types of microphones.

Although the solutions for some of these problems are more difficult to arrive at, none of them are intractable.

Conclusions and recommendations

Audio signal processing and classification can be a useful tool for monitoring poultry health status. It has the potential to extract useful information about poultry health status and their infection with respiratory diseases, without the need for any veterinary diagnostic testing. Respiratory diseases are the main threat to the health of poultry flocks. The proposed methodology is characterized by rapid, inexpensive, and continuous monitoring. The first step in developing a successful system is to record accurate sound signals. The signal processing system must then be able to separate the bird sounds from signals, produced by other sources such as environmental noises.

Finally, signal features that can distinguish the differences between healthy and diseased bird sounds should be extracted as the input features to the ultimate classifier. To distinguish these differences, a tool that is capable of comparing the bird calls with standard sounds is needed. There is evidence that wavelet transform has this ability. Once a complete database for healthy and diseased bird sounds is developed, an appropriate classifier can pave the way for its practical application. Meanwhile, a combination of machine-learning and classifier techniques can enhance the system's reliability and resolution. Such systems can be trained using a database certified by a veterinary lab, and can be practically used by poultry farmers. Although signal processing techniques can not currently extract accurate information about poultry health condition advanced, sound signal processing techniques have the potential of helping poultry farmers and veterinarians as an important diagnostic tool in the near future.

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