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Preliminary Acoustic Analysis of Farm Management Noise and Its Impact on Broiler Welfare

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† Presented at the 6th International Electronic Conference on Sensors and Applications, 15–30 November 2019; Available online: https://ecsa-6.sciforum.net/

Published: 14 November 2019

Abstract: Farm management practices done by machinery generate a high acoustical impact on animals. The acoustic variations in terms of equivalent level (L_{eq}) and the different types of noise can affect the well-being of broilers by means of reducing the food and water ingest. In this work, we create a dataset in which we conduct a preliminary analysis of the acoustical impact generated by the farm management in a intensive broiler poultry farm of 25,000 birds. The project collects acoustic data during the first two weeks of the birds life, focusing the study on the first week. To create the dataset we randomly select some files from each day of the study and they are analysed and labelled manually using an audio analysis software. The acoustical events defined in collaboration with the farmer and vet are fan, food and water supply, based on duration, impact and Signal to Noise Ratio (SNR). The analysis concludes that the main acoustical source in a broilers' farm is fan, and that it has an non negligible acoustical impact. Nevertheless, the most frequent acoustical noise source active is food supply, but with less L_{eq} impact.

Keywords: acoustic impact, L_{eq}, farm management noise, broiler well-fare, poultry farm.

1. Introduction

The food demand will be the double from the actual for the projected next 50 years [1]. The increase on demand of poultry meat since the past decade is due to the low cost, good nutritional profiles and suitability in farming [2]. Intensive production is required to achieve the demand and poultry health should be approached in a multidisciplinary way to ensure animal health [3]. According with OIE: An animal is in a good state of welfare if it is healthy, comfortable, well nourished, safe, able to express innate behaviour, and if it is not suffering from unpleasant states such as pain, fear and distress [4]. Some routine management practices are stressful to the birds [5] and it also result in an economic cost to the industry that cannot be ignored [6]. However, conventional methods for quantification of stress are not suitable indicators as they provide the detection only after it has negatively affected the animals [6].

In this first approach, we design the recording campaign in a farm, taking into account the several sounds caused by machinery. The farm noise is recorded, accurately labelled and processed using an non-invasive method, with the goal of analyzing the impact of several mechanization sounds in the farm to the background noise. Afterwards, we evaluate the number of occurrences, the duration of each sound and the Signal-to-Noise (SNR) as well as the acoustic equilvalent level impact (L_{eq}). In this sense, in the field of bioacoustics some technology has been designed to improve poultry welfare, for more details the reader is referred to [7].

This paper is structured as follows. The method and materials required to obtain the dataset and the corresponding process are detailed in Section 2. The database generation and the acoustic features used in this work are detailed in Sections 3 and 4 respectively. The discussion of the key aspects of this first approach is detailed in Section 5 and the conclusion and future work can be found in Section 6.

2. Materials and Methods

The preliminary acoustic analysis has been performed in a Mediterranean farm of 25,000 broilers during their first 9 days of life. The sounds emitted by the broilers and the farm machinery were recorded at one meter of the animals with one low cost microphone connected to a Raspberry Pi (3B) [8]. The design of the hardware of the project is inspired in [9], with a special focus in flexibility and adaptability of the model, as well as its capability of recording long audio sequences. The recording was made using a Python script coded with the open source library PyAudio available on [10]. The code recorded streams in a non-compression file system (wav) of 30 minutes continuously during the whole experiment using a 16 bits Digital-to-Analog Converter (DAC) and 44,100 KHz of sampling rate. The file generated was tagged with the day and time of the recording.

The identification of sound is done listening to the file, and observing the time-amplitude, spectrum and L_{eq1s} graph with Audacity, which is an open source program available on [11]. Acoustic evaluation and L_{eq1s} graph is executed to the labeled audio segments with Matlab, a program available on [12].

3. Farm Management Sound Database Generation

Poultry intensification requires the use of machinery to improve the efficiency of the farm management but it generates a moderate to high impact in the L_{eq} of the environmental noise. A dataset of all the noise generated by the farm mechanical equipment found in this first 9 days of observation has been generated. It is important in order to analyze the sound properties and the possible impact to the animals of all the types of noise, SNR, duration and occurrences.

3.1. Data Labeling

The raw sound recorded by the microphone contains acoustic events which some of them are complex to identify. The knowledge of a farmer and a vet have been required to correctly label the sound of fan, feeders, drinkers and the sound vibration of the bar of the feeders.

A manual labeling process has been conducted over 45 audio files, which corresponds to 22.5 hours of audio, labeled using up to 125 labels. The labeling method was not exhaustive over all the collected data, because that the aim of this first approach was focused on analysing the several different events occurring due to the farm management noise. The labeling was conducted with the goal of finding the types of events described by the farmer; nevertheless, once a file was being labeled, all the events were labeled with their proper name. The reader is referred to [13] for more details of the data labelling.

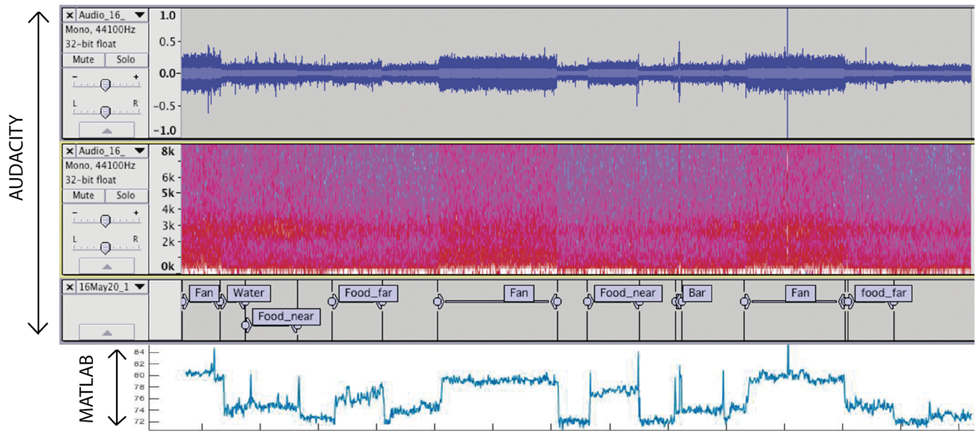

Figure 1. Capture of the data labeling process using Audacity [11] and Matlab [12]. A time-amplitude, spectrum and L_{eq1s} graph is required to identify the classes.

Figure 1 shows an example of the labeling process. Audacity [11] shows time-amplitude and spectrum graph and a Matlab [11] figure presents the equivalent level of the same audio segment. In the Spectrum view identifies clearly fan, bar vibration and water class due to the frequency distribution of the noise. The L_{eq1s} is important to identify the beginning and ending of each label. Food noise identified by the impulse at starting and end in the time-amplitude and L_{eq1s} graph as there is not a clear spectrum identification. The process of listening is a crucial stage before labeling to ensure the audio corresponds to the visual identification of the class.

3.2. Data Classes Defined

Five classes have been clearly identified apart from the background noise according to the farmer indications. The fans, feeders, drinkers and lights are activated and disabled automatically depending of the farmer rules introduced in a smart system depending on the temperature, humidity, hours of rest among others. After the examination of several samples of the feeder noise it has been observed that acoustic levels varies in function of the location of the sound source in two blocks due so it has been split between two classes.

Data labeled is classified as: Fan Sound generated by the blower blades and motors; Food close Sound generated by the food load of the feeder near to the microphone; Food far Sound generated by the food load of the feeder far to the microphone; Water Sound generated by the water load of the drinker; Bar vibration Structural vibration of the bar of feeder captured where the microphone is hold. The list of classes in function of the number of files segmented and the duration of the samples of each category are shown in Table 1.

Table 1. Audio samples obtained after segmentation.

Class	Number of samples	Total duration (min)
Fan	30	154.05
Food close	38	39.1
Food far	39	27.03
Water	15	32.69
Bar vibration	3	9.85
Total	125	262.72

4. Acoustic Para Evaluations

Three parameters were taken into a count to describe each event. The first parameter describes how persistent in time the noise is the duration. The second metric is based on calculating the SNR, the resultant value indicates the ratio of the power of the event in relation of the power of the background saliency. The last metric determines the impact of the event on the equivalent L_{eq} noise level. The calculation of each feature is described below, and the reader is referred to [14] for more details.

4.1. Duration Measurement

The duration of the event is calculated as the difference between the starting temporal stamp and the ending one. The duration of the event depends on the typology of the sound and the conditions of the farm as the machinery is activated automatically.

4.2. SNR Calculation

The calculation of SNR is defined considering the event not stationary. The pressure level is calculated as the Equation (1) where N is the number of samples and $x(t)$ is the piece of the audio segmented of the event.

$$P_x = \sum_{t-1}^{N} \left(\frac{x(t)^2}{N} \right) \tag{1}$$

SNR is defined as below where P_{event} is the acoustic power of the class event and P_{bkn} is the acoustic power of the previous and latter segments of the class with background noise only.

$$SNR = 10 \log_{10} \left(\frac{P_{event}}{P_{bkn}} \right) \tag{2}$$

Note that the SNR (see Equation (2)) could be negative if the power of the background noise near the event is higher than the power of the event itself. This may happen with low-energy sounds like the *water* class.

4.3. Impact Calculation

The impact determines the contribution of an individual event to the equivalent noise level calculated during the 30 minutes of the audio file. It is computed as calculating the difference (see Equation (3)) of the $L_{eq,event}$ of the segment with the event and the $L_{eq,\overline{event}}$ of the same audio segment replacing the event with a linear interpolation from the first to the last sample of the original data. Find a more detailed calculation explanation in [13,14].

$$\Delta L_{eq} = L_{eq,event} - L_{eq,\overline{event}} \tag{3}$$

5. Discussion

We have evaluated the parameters of the acoustic data as detailed in Section 4 and the results obtained are shown in Table 2. The data has been collected in a standard production cycle according to the Spanish regulation [15]. The temperature and humidity have been monitored between 39–34 °C and 51–40 % respectively.

Table 2. Metrics detail for each acoustic class.

Classes	Duration (min)			SNR (dB)			Impact (dB)		
	Diurnal	Nocturnal	Daily	Diurnal	Nocturnal	Daily	Diurnal	Nocturnal	Daily
Fan	5.135	-	5.135	6.434	-	6.434	1.177	-	1.177
Food close	0.567	1.330	1.029	3.269	7.419	5.690	0.157	0.173	0.166
Food far	0.644	0.731	0.693	2.408	3.152	2.822	0.026	0.091	0.051
Water	2.863	1.582	2.180	0.247	0.253	0.250	-0.047	0.011	-0.005
Bar vibration	4.819	0.218	3.285	3.762	3.026	3.516	1.351	0.035	0.912

The results shown in Table 2 correspond to the mean value of each metric (duration, SNR and impact) during the first nine day of broilers' life and using the aggregated data of diurnal, nocturnal and daily data files.

Fan presents the longest event (5.13 min) also the one with better SNR (6.43 dB) and with a high impact (1.177 dB); the fact that it does not activate during the night contributes in the rest of the animals. Following the most impact class, is Bar vibration with also long duration (4.8 min) mostly during day, and high SNR (+ 3 dB) and the highest impact (1.35 dB). Food close and Food far reduces the duration by comparison with the previous mentioned and there is a higher demand (in duration) in the course of the night, SNR is higher in the close class and it is a better metric as impact is null. On the other side, Water is the event with less impact as it has a SNR and impact metric negligible.

In Figure 2 we can observe the SNR, the impact and the duration of all the events labelled by class. Three big areas are spot. First area contains events of less than 40 seconds some Food far, Food near and Water with negligible SNR and impact; we could set the hypothesis that these events do not affect the animals. The small circles are due to the negative values of impact. Second area contains events between more than 40 to less than 100 seconds divided into two subareas with less than 6 dB in SNR (first part) and the other subarea (second part) with high SNR and impact (which corresponds to the night events). In all these area the classes identify are Food far and Food near. Third area events with more than 100 seconds corresponds to Fan and Bar vibration which SNR and impact values are the highest of the other events.

Notice that in the second area there is the most density of classes occurrence with non negligible values. Reducing the number of this events would reduce the acoustic impact to the animals substantially.

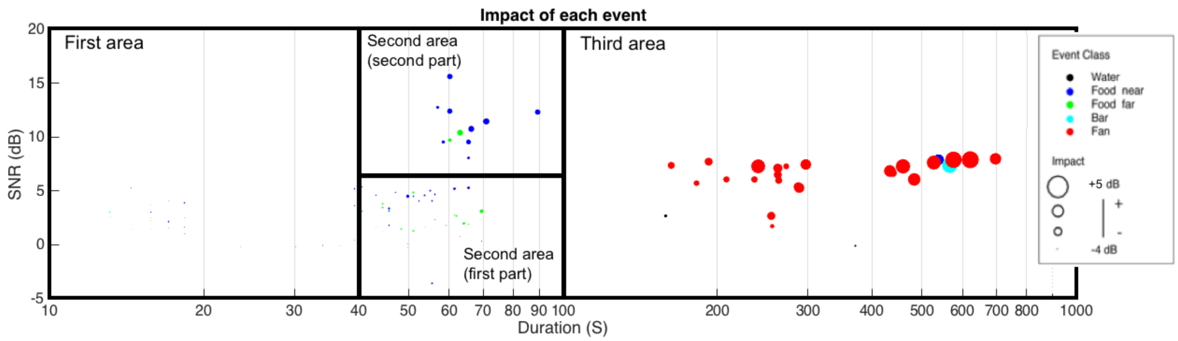

Figure 2. SNR, impact and duration graph per each class.

Based on the data analysed, the classes can be sorted by the acoustical impact with the following order.

$$Fan \geq Bar\ Vibration \geq Food\ close \geq Food\ far \geq Water \tag{4}$$

6. Conclusion and future work

The dataset obtained in this work during the first 9 days of the broilers' life is a first approach to the noise distribution in a farm due to the the farm management noise. The acoustic event with higher impact is *Fan* with mean values of 5.13 min of duration, 6.43 dB of SNR and 0.94 dB in impact. *Fan* can not be reduced in terms of usage as it reduces the concentration of gas decomposition among others inside the farm, but can be redesigned to generate less noise in terms of equivalent level L_{eq}. The most frequent noise is the food supply with a non negligible metric values, the repetition of the same noise constantly reduces the silent intervals as broilers grew and also augment the ingest of food, activating more frequently the feeder.

This preliminary data results have to be further on studied. Future work will be focused on collecting more acoustic data of the whole production cycle (six weeks) to study the broilers growth and the effect of their singing modification on account of farm management and correlating this data with gas emissions and broilers decease.

Author Contributions: Gerardo Ginovart-Panisello led the field work collecting the audio data, labelling, processing the dataset and participated in writing the entire paper. Rosa Ma Alsina-Pagès has supported the signal processing part and participated in writing and reviewing of the entire paper.

Funding: This research has been co-financed by Cealvet SLu

Acknowledgments: The authors would like to thank Tesa Panisello for supporting the project, helping in the design and executing the field work and Josep Maria Mensa for their knowledge and letting us study their broiler farm.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DAC	Digital to Analog Converter
L_{eq}	Equivalent pressure level
OIE	World Organisation for Animal Health
P_{bkn}	Acoustic power of the background noise near event.
P_{event}	Acoustic power of a class event.
SNR	Signal to Noise Ratio
WAV	Windows Wave

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