CLASSIFYING BROILER CHICKEN CONDITION USING AUDIO DATA

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ABSTRACT

This paper is an effort to help prevent broiler chicken mortality caused by stressful conditions. We assume a relation between broiler chicken vocalizations and stress; therefore, microphones were used to monitor a flock of birds over the course of their lifetime (approximately 65 days). A noise removal method based on spectral oversubtraction was developed to filter out the significant fan and heater noise and shown to be very effective. Then, a radar processing technique was employed to count the number of vocalizations. It was found that the number of vocalizations is an effective technique for detecting stressful conditions, easily classifying the gathered test cases using a threshold classifier with perfect accuracy. Therefore, we conclude that this system could easily be adapted into an effective, inexpensive poultry flock monitoring tool, and the methods developed here could be applied to other similar monitoring applications.

***Index Terms*—** food industry, signal processing algorithms, noise cancellation, additive noise, adaptive signal processing

1. INTRODUCTION

Broiler chickens, the most common type of chicken raised for meat production, constitute a large part of the poultry industry, with 8.55 billion broilers being raised in 2009 in the United States alone. Occasional equipment failures or errors will cause stress in the birds, causing suboptimal growth or even death in some situations. With the average broiler chicken having little resistance to thermal variance, bird mortality due to heat stress is a significant concern for the poultry industry.

In spite of advanced temperature and environment monitoring sensors, the possibility of situations causing broiler stress and mortality still exists. In this paper, we use audio data from a grow-out house to show that broiler stress can be reliably determined by the use of signal processing techniques.

Audio processing has been applied to other animal classification tasks. The most popular application has been bird song recognition [1, 2], but there are other examples. For instance, the Dr. Doolittle project [3] attempts to classify animals based on their vocalizations. In another instance, sound source localization was used to detect respiratory diseases in pig houses [4], and bird song recognition has long been a popular goal [1, 2]. However, the use of audio processing to classify the condition of broiler chickens is, to our knowledge, a novel concept. In this paper, it is shown that audio data can be used to classify when broiler chickens are under a stressful condition.

2. DESCRIPTION OF EXPERIMENT

For this experiment, audio data was collected from two stereo microphone sources in a grow-out house at the University of Georgia over the entire lifetime of the flock. During this period, food and water are readily available to the birds at all times. The lights in the room (in this particular room there were no windows; this is not standard for the industry) were on from about 5 a.m. to 1 a.m. each day.

Data was collected at 96 kHz with 24-bit samples. During the last few days of the experiment, the temperature was manually set to approximately fifteen degrees Fahrenheit above the usual temperature of the grow-out house, thereby stressing the birds. This stressing procedure was performed for six days, for approximately three hours per day (at all other times, the birds lived under normal environmental conditions).

The audio data was also corrupted with several environmental noises. The grow-out house had three loud fans; a ceiling fan, and an upper and lower ventilation fan. In addition, an audible heater was occasionally running. Also, the doors to the house would occasionally open and close as maintenance workers ensured that the environment was acceptable for the birds. All of these sounds are clearly audible on the recordings and in some cases drown out bird noises entirely.

3. NOISE REMOVAL

Several options are available for removing noise from recordings. The Dr. Doolittle project [3] uses Ephraim-Malah noise suppression [5] successfully. However, Ephraim-Malah enhancement does not entirely remove the noise. We can design a more effective filtering method, based on spectral subtraction using minimum statistics [6].

The spectral subtraction idea oversubtracts a spectral estimate of the noise from the short-time Fourier transform (STFT) frames of the signal. The oversubtraction factor is used to suppress any residual noise. To gather the noise estimate, a voice activity detector is used to find sections of the signal that are noise-only. After the noise estimate is subtracted from the signal, the filtered signal is reconstructed using the WOLA (windowed overlap-add) technique. A block diagram of this scheme can be seen in Figure 1.

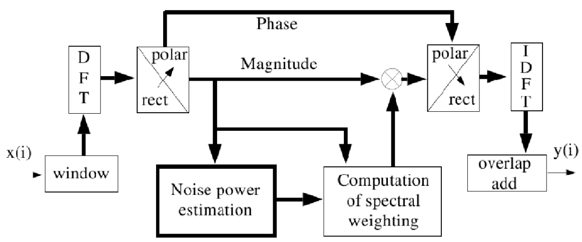


Fig. 1. Block Diagram of Spectral Oversubtraction System.

To adapt this to our system, we would need a voice activity detector (VAD). The use of a VAD is unfeasible for our scenario, because hundreds of birds are making a noise at any time. An analysis of an individual vocalization shows that each vocalization is essentially instantaneous (50 ms or shorter), and will only show up in one or two STFT frames. Our noise from the fans, on the other hand, is slow-changing and will not cause sudden changes in the STFT magnitudes.

Therefore, if we assume that in the context of our noise estimator every frame is noise, then we can assemble a moving noise estimate from the last several frames:

$$\hat{W}(k,n) = \frac{1}{m}\sum_{i=0}^{m} S(k,n), \tag{1}$$

where $S(k,n)$ represents the magnitude bin k of the nth STFT frame of the signal. Accordingly, $\hat{W}(k,n)$ represents bin k of the noise estimate magnitude for frame n. The parameter m controls the length of the average. In practice, the best results were obtained for $10 < m < 100$.

Using this noise estimate we can then estimate the clean STFT frame using spectral oversubtraction, disallowing any negative magnitudes:

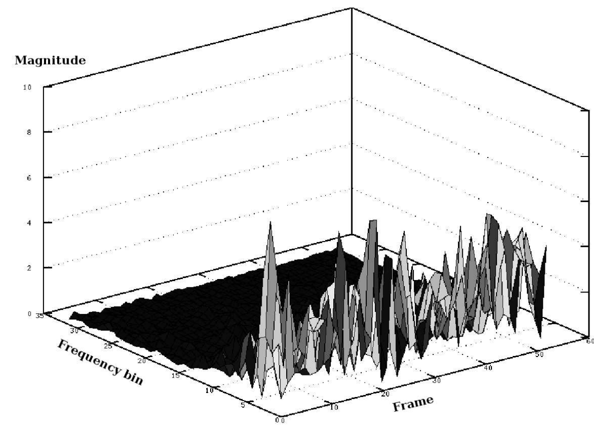
$$\hat{X}(k,n) = \max(S(k,n) - \alpha\hat{W}(k,n), 0) \tag{2}$$

with α as the oversubtraction parameter.

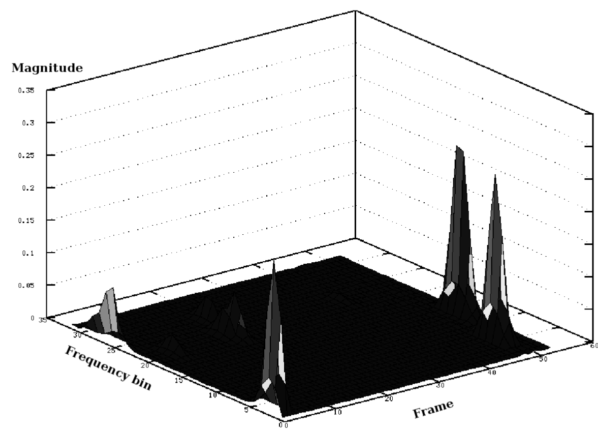
The phase of the original frame estimate is not modified during the oversubtraction process. After oversubtraction, windowed overlap-add is used to reassemble the clean signal.

3.1. Results

Figure 2(a) shows a 3D plot of STFT frames over time for an unmodified signal taken from a data segment when multiple fans were on. Figure 2(b) shows the same segment after noise removal using $\alpha = 2.5$ and $m = 10$.



(a) Unmodified signal



(b) Noise removed with oversubtraction factor of 2.5

Fig. 2. STFT frames over time for noisy and filtered data.

Clearly, the majority of the signal is suppressed, leaving only a few sparse components. Upon reconstruction and listening, it is clear that these components are the bird vocalizations; and the fan noise is significantly reduced. In fact, with the exception of minor residual noise introduced by the noise removal process, the enhanced audio is almost identical to a clean segment of audio (taken from when no fans or noise disturbances were present).

The oversubtraction factor α was found to provide the best trade-off between noise suppression and signal preservation at a value of 2.3. Higher values removed the bird vocalizations, while smaller values allowed fan noise to remain in the output.

With the audio effectively filtered and noise no longer a problem, we can move on to the problem of condition classification.

4. BROILER CONDITION CLASSIFICATION

An informal discussion with farm hands and knowledge of broiler chickens suggested that the birds make more noise when under stress. However, a simple measurement of the power in spectral data was not effective, likely due to some residual noise introduced by the filtering process.

Therefore, a different approach, inspired by radar processing techniques [7], was employed. In this approach, individual vocalizations are detected and counted. Detections are found using a simple thresholding technique. At each STFT frame, any bins above a certain predefined magnitude threshold are marked. The bin (and its two neighbors) are checked in the next frame, and if any of those are above the threshold, they are also marked. This process continues until a frame where neither the bin nor its neighbors are over the threshold. This series of above-threshold frames constitutes a single detection. It is important to note that we have allowed the frequency of the detection to change over time by one bin per frame.

In addition, we further constrain the allowed detection to be within the likely range of frequencies for a bird; low frequencies are ignored (to avoid any remaining fan noise) and very high frequencies are also ignored.

This detection algorithm was then run over the entire dataset. Figure 3 shows the average number of bird vocalizations in a 45-minute period over the course of a day when the birds were not intentionally stressed (the x-axis represents the hour during the day).

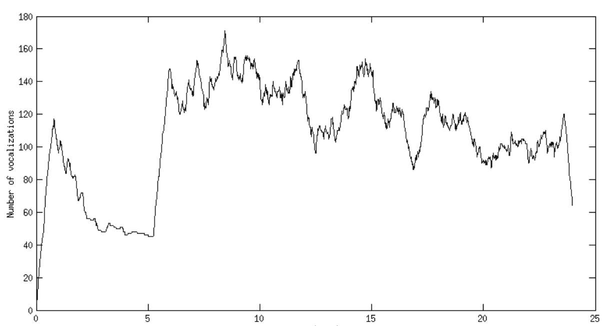


Fig. 3. Number of vocalizations per 45-minute period in an average day.

During the hours when the lights are off (hours 1 to 5), the number of vocalizations drops significantly. When the lights turn back on, the birds immediately start making noise again. The number of vocalizations over the rest of the day is somewhat variable, but still reasonable.

In Figure 4, we have plotted three days of unstressed data alongside three days of stressed data. It is very clear which days (and even which times during the day) the birds were stressed. A closer analysis of the experiment logs show that the periods with a large number of vocalizations (> 200) correspond almost exactly with the periods of increased temperature. The raised temperature occurred approximately during hours 10 to 12 on two of the plotted stressed days, and approximately during hours 13 to 15 on the other plotted stressed day. A "recovery period" after the stress condition is also visible.

By applying a threshold at 200 vocalizations in a 45-minute period, we find that we can detect each of the stressful situations the birds encountered within 20 to 30 minutes. Unfortunately, we can only verify the success of this method for our admittedly few test cases; however, obtaining test audio data for these situations is difficult due to animal welfare regulations.

5. CONCLUSION

By using a spectral oversubtraction method in combination with a vocalization detection algorithm, we have shown that we can effectively detect stressful conditions in broiler grow-out houses.

Our spectral oversubtraction method, operating under the assumption that individual vocalizations will not significantly affect a moving average of STFT frames (which is used as a noise estimate), removes almost all interfering noise from the data. However, this method is not likely to be applicable to many other situations; it is specialized to this particular application.

The vocalization detection algorithm, which counts individual vocalizations, provides a clear feature which can reliably be used to classify the existence of a stressor condition. In addition, the algorithm is very simple and could be implemented in real-time. This algorithm could be coupled with the spectral oversubtraction method (since that is also STFT-based analysis) and implemented on a low-power real-time system, allowing industry grow-out houses to have a cheap yet reliable monitor on their flocks.

Unfortunately, since we were only able to monitor and stress one flock, more data should be gathered, in different settings. Most grow-out houses are similar, but it should be verified that the techniques that worked in this house generalize to other settings. More instances of stressors are also required to verify that the birds will always respond in the same way (more vocalizations). However, we expect that the methods described in this paper will also be effective in other grow-out house situations.

This work also opens up a possibility of hatchery monitoring, which is a similar situation. The objective is to detect when eggs start hatching; fan noise is also prevalent in this setting. The noise of the hatching eggs (the birds tapping their

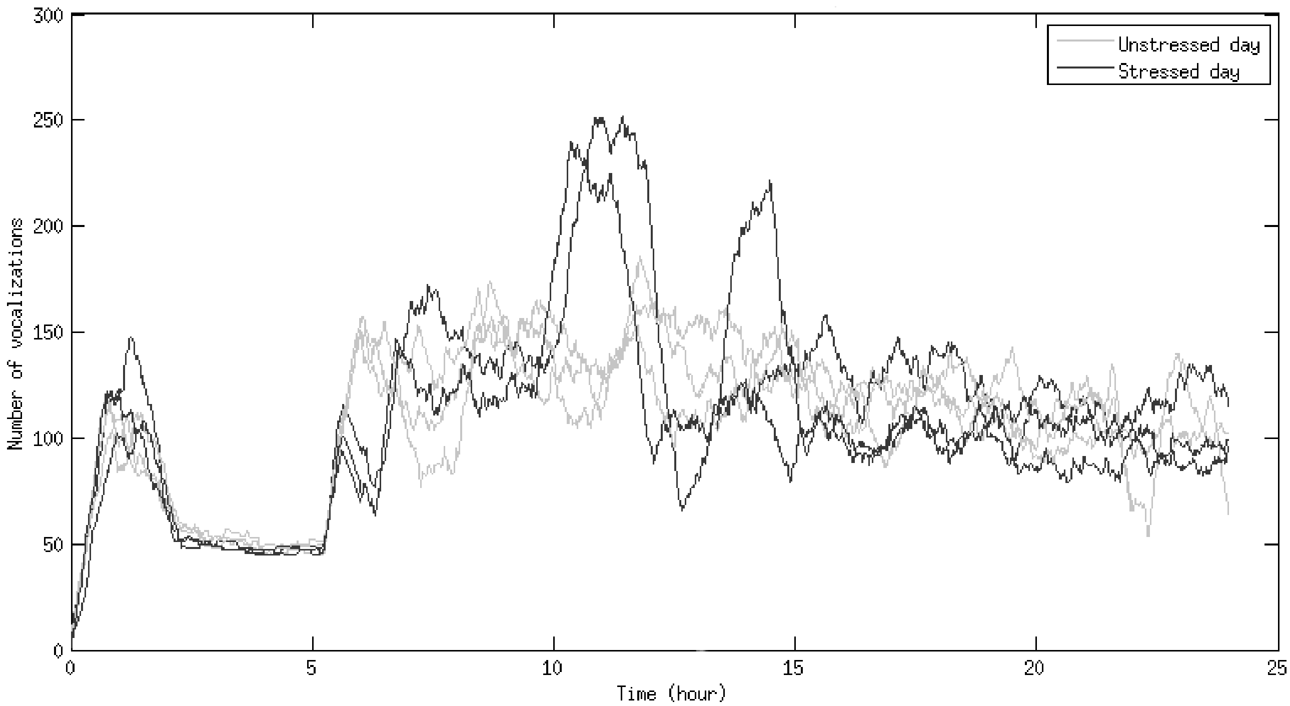


Fig. 4. Number of vocalizations for both stressed and unstressed days.

beaks against the shell) is very short-term, meaning that the filtering method described above is likely to be effective. Investigation into this topic has already begun, and results are forthcoming.

6. REFERENCES

[1] P. Somervuo and A. Harma, "Bird song recognition based on syllable pair histograms," *IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 5, no. 17, pp. 825–828, 2004.

[2] J.A. Kogan and D. Margoliash, "Automated recognition of bird song elements from continuous recordings using dynamic time warping and hidden marjove models: A comparative study," *Journal of the Acoustical Society of America*, vol. 103, no. 4, pp. 2185–2196, 1998.

[3] M. Johnson, A. Savage, M. Darre, P.M. Scheifele, and E. Muggenthaler, "Dr. Doolittle Project," 2009, http://speechlab.eece.mu.edu/dolittle/index.html.

[4] M. Silva, S. Ferrari, A. Costa, J.-M. Aerts, M. Guarino, and D. Berckmans, "Cough localization for the detection of respiratory diseases in pig houses," *Computers and Electronics in Agriculture*, vol. 64, no. 2, pp. 286–292, 2008.

[5] Y. Ephraim and D. Malah, "Speech enhancement using a minimum-mean square error short-time spectral amplitude estimator," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 32, no. 6, pp. 1109–1121, 1984.

[6] R. Martin, "Spectral subtraction based on minimum statistics," *EUSIPCO*, pp. 1182–1185, 1994.

[7] J. Tsui, *Digital Techniques for Wideband Receivers*, SciTech Publishing, 2nd edition, 2004.