COUGH ANALYSIS AND CLASSIFICATION BY LABELLING SOUND IN SWINE RESPIRATORY DISEASE

M. Guarino[1], A. Costa[1], S. Patelli[1], M. Silva[2], D. Berckmans[2]

[1]Department of Veterinary and Technological Sciences for Food safety, Faculty of Veterinary Medicine, via Celoria, 10, 20133 Milan, Italy

[2]Laboratory for Agricultural Buildings Research Katholieke Universiteit Leuven, Kasteelpark Arenberg 303001 Leuven, Belgium

I. INTRODUCTION

Coughing is one of the most frequent presenting symptoms of many diseases affecting the airways and the lungs of both humans and animals. In piggeries, the continuous on-line monitoring of cough sound can be used to build an intelligent alarm system for the early detection of diseases [1,2,3]. In a first study, with experiments under laboratory conditions, algorithms have been developed to detect cough sounds and to classify the animals whether they were ill or not. In this study, the algorithm was tested in field conditions.

Sound analysis is an interesting method to monitor health status since it needs no physical contact with the animals. Moreover the used microphone in these tests is a very cheap type.

When a pig is infected with a respiration disease, the respiration system is changing, causing the characteristics of the air going through the air pipe to produce a different sound. When it is possible to monitor and analyze the sound of a cough signal, an on-line disease monitor can be developed.

A main application is early detection of disease to reduce the use of antibiotics. In previous studies, an accurate algorithm is presented to detect citric acid induced coughing originating from healthy individual piglets. An intelligent free field recognizer is proposed to distinguish between coughing, evoked in absence or presence of a respiratory infection.

Health care management is a critical and demanding issue in current livestock production. Discarding the economic cost related to large scale diseases, early detection of diseases is important considering public health care issues like reducing antibiotics residuals. Also for reasons of animal welfare and monitoring and tracing of the food production chain, online disease monitoring is important. Therefore currently great effort is spent to the development and application of sensors and sensing techniques for diagnosis in the agricultural sector [4]. With respect to objective and automated detection of respiratory diseases in livestock, it has been shown that artificial intelligence is successfully applicable to obtain automated cough recognition from free field cough recognition.

In the work of Van Hirtum and Berckmans [6] an accurate algorithm is presented to detect citric acid induced coughing originating from healthy individual piglets under laboratory test conditions. In their work an intelligent free field recognizer is proposed to distinguish between coughing evoked in absence or presence of a respiratory infection. A drawback of the developed algorithm is that it is time consuming to run, what can cause problems when applying it in practice. Furthermore, the results are obtained on a database which is registered on individual subjects housed in a laboratory test-installation consisting of a laboratory inhalation-chamber. The test-installation, described by Van Hirtum and Berckmans [6] and Urbain et al. [7], allows to control environmental housing conditions, medical follow-up and to reduce environmental noises. So cough sounds are registered in optimal environmental sound conditions. Therefore the performance of the developed algorithms to recognize cough in field conditions needs to be assessed in order to validate the usage of sound analysis in livestock health management.

To this purpose, in a previous study [8], coughs were registered in field conditions keeping one microphone near the animal.

In that study, limiting the spectral frequency to the range from 2 kHz to 14 kHz allowed to eliminate low-frequency noises from mechanical origin, while the cough sound exhibited an important energy-peak in this range.

The main objective of this study was to evaluate the accuracy of cough recognition algorithm on labeled coughs from all other sounds, recorded simultaneously with background noises using two microphones, one for noise and one for cough recording.

II. METHODOLOGY

Animals: 350 pigs (commercial crosses) were in the first period of the finishing phase, their mean weight at the beginning of the trial was around 75 kg and their mean age was 170 days. The fattening room was wide 14 x 21,10 m and was divided in 16 boxes with totally slatted floor.

Models and analysis of vocal emissions for biomedical applications. 4th international workshop. October 29-31, 2005 – Firenze, Italy.
Edited by C. Manfredi. ISBN 88-8453-320-1 (online)

The walls were made of concrete bricks and insulated (PVC thick sheet) and the roof is made of prefab plates of concrete. Roof inclination was 30 %.
A serological assay on blood sample to verify the presence of Pleuropneumonitis antibodies has been conducted on sick pigs to verify the source of coughing. After the slaughtering, Pleuropolmonitis was confirmed by the autopsy examine performed by the farm veterinarian.
Measurements: Pigs cough was recorded using a microphone linked to the PC sound card (Conexant, AC link audio16 bit).. This was done to record the cough sound in practical field conditions, without taking the acoustical characteristics of the stable into account. The recordings were made at a sample rate of 44100 Hz, with a resolution of 16bits. The coughs were sampled with a frequency of 22050Hz to gain calculation time.
The microphones where placed in the middle of the room, in the corridor, at 3 m and 18 m far from the entrance door. The data, collected in 5 days in a piggery, were labeled first by a veterinarian and then re-labeled in laboratory. The main objective of these tests was to evaluate the accuracy of cough recognition algorithm on labeled coughs from all other sounds. In the dataset there was a total of 396 different sounds.
Cough analysis: To visualize a sound the amplitude can be plotted in time. This representation method doesn't give any information about the frequency characteristics. In a spectrogram, the signal is analyzed using Fourier transformation in order to show how the frequencies change over time.
An example of an amplitude-time representation of a cough is given in figure 1.

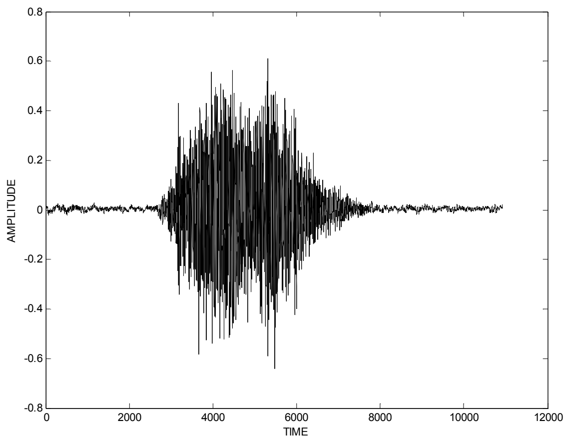

Figure 1. Amplitude variation in time (in samples) of a cough signal

The Spectrogram of the same signal is shown in figure 2.
The signal represented in figure 1 was a typical cough sound of a pig, the duration is only 0.7s.

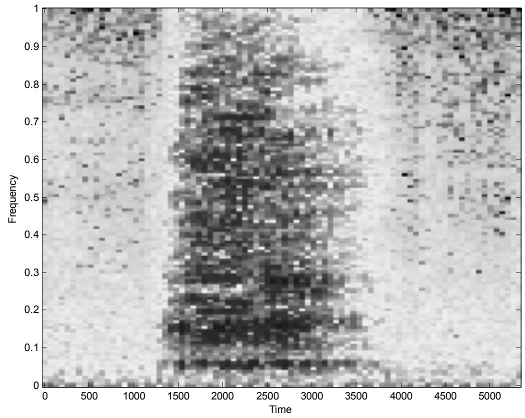

Figure 2. Spectrogram of the cough signal represented in figure 1.

<u>Classification of the sounds:</u>

In order to classify a sound, it has to be compared with a reference sound.

This is done using a method called "dynamic time warping", already used successfully in a previous work (Van Hirtum et al., 2003), in which each sound is divided into frames of equal length and the features of each frame are stored in a feature vector. Thus, each sound is represented by a sequence of data feature vectors that form a sound template. The different duration of the cough sound results from non-uniform stretching and compression of the various portions in the cough sound. Consequently simple linear time alignment is not appropriate to compare two sounds of unequal duration. In order to compare two sound templates, the DTW algorithm uses one of them as a test pattern and the other one as a reference pattern. Taking frame by frame of the test sound template, DTW looks for the frame-path in the training template that results in the minimum distortion. For each test frame a set of specified frames in the training template is allowed for comparison.
Now, to test whether or not a certain sound is part of a specific class (cough, grunt, sneeze,…) the labeled sounds are divided into two groups: one test set and one training set.
Every sound in the test set is compared with all the sounds in the training set. If, at least, half of the sounds in the training set classifies the tested sound as a cough, the tested sound is marked as *cough*. If, on the other hand, more than half of the sounds in the training set classify the tested sound as non-cough, the sound is assumed *not cough*.
In order to have a good idea of the performance of the algorithm that was used to recognize the sounds, a method is required that shows how many sounds where classified in the correct way. This involves the number of coughs that were classified as coughs out of the total set

of cough sounds as well as the number of other sounds (grunts, screams, sneeze) that were classified as non-coughs out of the total set of non-cough sounds. So the performance of correct cough classification (P_{CC}) can be written as:

$$P_{CC} = \text{Nr. of correct cough classifications/ Nr. of total cough sounds}$$

In the same way, the performance of the algorithm to classify other sounds as non-coughs (performance of correct non-cough classification, P_{NCC}) can be written as:

$$P_{NCC} = \text{Nr. of correct non-cough classifications/ Nr. of total non-cough classifications.}$$

The total performance (TP) can then be written as:

$$TP = (P_{CC}+P_{NCC})/2$$

To have a representative performance of the algorithm, the test set and the training set are defined as followed: The test set consists of 10% of the total amount of sounds to be classified. The training set consists of 90% of the cough sounds. With this 10 % of the test set, 10 % of the 'other' sounds are mixed, to have a representative snap check. A permutation is applied 10 times, until all cough sound have been in the test class. The number of miscalculations is counted in order to have an estimate of the performance of the algorithm.

III. RESULTS

An overview of recorded sounds is given in table 1.

Although the average performance of the algorithm for cough sounds is about 72,6 % (see Figure 3), while the performance for other sounds, including sneezes, grunts, sounds of doors being opened and screams, is about 61.7% (see Table 2), this is a first step in a fully automated cough recognition system for the monitoring of swine epidemics.

Sound files:		
	coughs	186
	grunts	67
	screams	62
	doors, noise..	40
	sneezes	41
Total		**396**

Table 1: an overview of the data on which the cough recognition algorithm is tested.

It is possible to see the variation in cough recording accuracy depending on the day of observation, due probably to different environmental conditions.

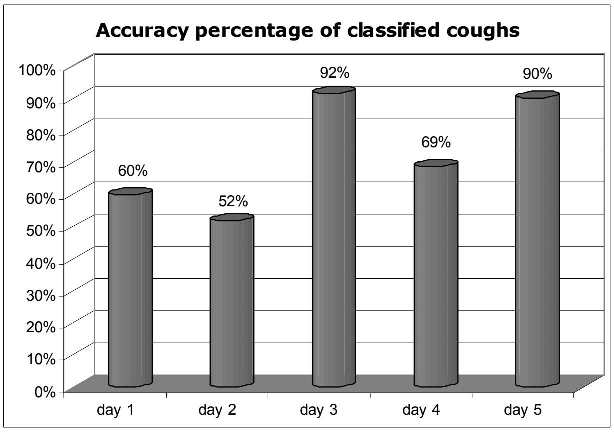

Figure3. Average performance of the algorithm for cough sound recognition.

Days	Sounds correctly classified / Total sounds	Correct classification %
Day 1	29/60	48,33%
Day 2	19/42	45,24%
Day 3	21/40	52,50%
Day 4	104/157	66,24%
Day 5	174/239	72,80%
TOTAL	347/538	61,77%

Table 2. Average performance of the algorithm for sounds recognition.

The sounds of pig cough and noise background recorded of good quality are presented in figure and bad quality tracks in Figure 4 and 5 respectively.

IV. DISCUSSION

It is expected that better results will be obtained with different electronics.

Although the algorithm is tested off-line in this study, a fully automated recognition system involves an on-line application of the algorithm. A possible method of doing so is by, simultaneously as the sound information is acquired, letting a window of a certain sample length slide across this incoming sound. By detecting energy within this time frame, the algorithm could decide whether or not the signal in the frame is of interest for further processing. A method for classifying the different sounds may be a similar approach as the one that was followed in this study. Though, a drawback of this system is that the training set of the sounds should encounter as much as variability in order to have a good classification performance.

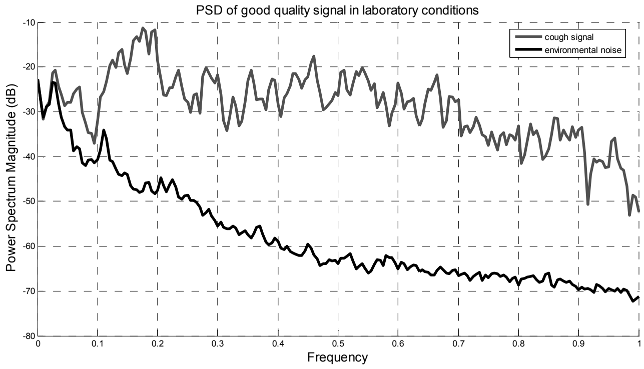

Figure4: PSD of a signal acquired from a good quality recording. The black line represents the cough signal,, the grey line represents the noise in that signal.

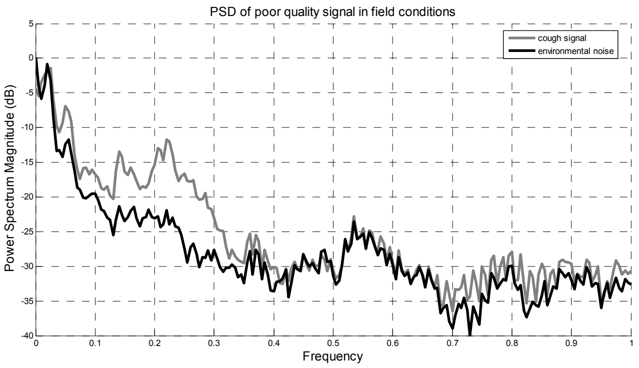

Figure 5: PSD of a signal acquired from a bad quality recording. The black line represents the cough signal, the grey line represents the noise in that signal.

V. CONCLUSION

In the future other methods for classification should be examined. For example, using sound models that serve as a "template" of a certain sound.

These models can be "mapped" onto the specific sound and by adjusting the model parameters, it might be possible to search for the best model of a certain sound. One might conclude that online model based sound analysis has a high potential for animal monitoring, but there is much to be done before such a fully automated on-line sound classification system can reach the daylight.

This research could lead, in future, to a real time automatic system of cough recognition in piggeries, that might be useful in preventing the spreading of respiratory diseases and lowering the excessive use of antibiotics in pig management. The algorithm presented here can be seen as a start to extrapolated existing techniques of voice analysis towards less conventional "sounds" as coughs, grunts and pig screams. Although some research has been performed on cough analysis, the applications remain poor. By applying such experiments in field conditions, it might bring this approach of bio-acoustics as a possible disease monitoring system closer to reality. In this case the object is the swine, but this can easily be expanded to other species like cattle and poultry.

REFERENCES

[1] A. V. Hirtum and D. Berckmans, "Objective recognition of cough-sound as biomarker for aerial pollutants," International Journal of Indoor Air Quality and Health, in press.

[2] Hiew Y., Smith J., Earis J., Cheethma B. and Woodcock A., "Dsp algorithm for cough identification and counting", Proc. ICASSP '02, Orlando, Florida, pp. 3888-3891, 2002

[3] Aerts JM, Jans P, Halloy D, et al. Labeling of cough data from pigs for on-line disease monitoring by sound analysis. Transactions of the ASAE 48 (1): 351-354. Jan-Feb 2005

[4] I. Tothill, "Biosensors developments and potential applications in the agricultural diagnosis sector," Computers and Electronics in Agriculture, vol. 30, pp. 205-218, 2001.

[5] V. Hirtum, A. and Berckmans D., "Fuzzy approach for improved recognition of citric acid induced piglet coughing from continuous registration", J. Sound and Vibration, vol. 266, pp. 667-686, 2003

[6] V. Hirtum, A. and Berckmans D., "Intelligent free field cough sound recognition", Proc. ICONS '03, Faro, Portugal, pp. 453-58, 2003

[7] B. Urbain, J. Provoust, D. Beerens, O. Michel, B. Nicks, M. Ansay, and P. Gustin, "Chronic exposure of pigs to airborne dust and endotoxins in an environmental chamber," Veterinary Research Communications, vol. 27, pp. 569-578, 1996.

[8] A. Van Hirtum , M. Guarino M., A. Costa., P. Jans., K. Ghesquire, D. Berckmans, P. Navarotto. 2003. Automatic detection of chronic pig coughing from continuous registration in field situations. Proceedings of the 3rd International Workshop on Models and Analysis of Vocal Emissions for Biomedical Applications. Florence 10-12 Dicembre 2003. pp. 251, 254.