DEVELOPMENT OF AN ALGORITHM FOR IN FIELD DETECTION OF PIG EPIDEMICS USING COUGH SIGNALS

Marcella Guarino, Annamaria Costa, Philippe Jans, Mitchell Silva,Jean-Marie Aerts, Daniel Berckmans

KULeuven, Department of Agro-Engineering and Economics, Laboratory for Agricultural Buildings Research, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium;
Correspondent address: Daniel.Berckmans@agr.kuleuven.ac.be

Key words : cough recognition, online health monitoring, sound classification, pig health

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. 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 aim was to test the algorithm in field conditions.

Materials and methods

Animals

The pigs (Landrace x Large White x Duroc crosses) were in the first period of the finishing stage, their mean weight was around 60 kg, their mean age 150 days. A serological assay has been conducted on a blood sample of the sick pigs, to verify the presence of Pleuropneumonitis antibodies, to verify the source of coughing. After the slaughtering, Pleuropneumonitis was confirmed by the autopsy examine performed by the farm veterinarian.

Measurements

Experimental data were obtained in swine housing for finishing pigs assigned to the Parma ham production in Northern Italy. Pigs cough was recorded using a microphone linked to the sound card of a portable computer. The operator, standing in the box, among the pigs, recorded the coughs putting the microphone at 20-50 cm from the animal. 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 22050 Hz, with a resolution of 8 bits. In total, 44 cough attacks, all observed in different files, have been recorded from 44 different animals, which is almost 4 hours of data.

Algorithm

To distinguish all sounds from cough sounds we need to consider specific characteristics of the sound or so called "features". To create a vector containing these features we use 4 steps. The 4 signal analysis steps are schematically illustrated in figure 1:

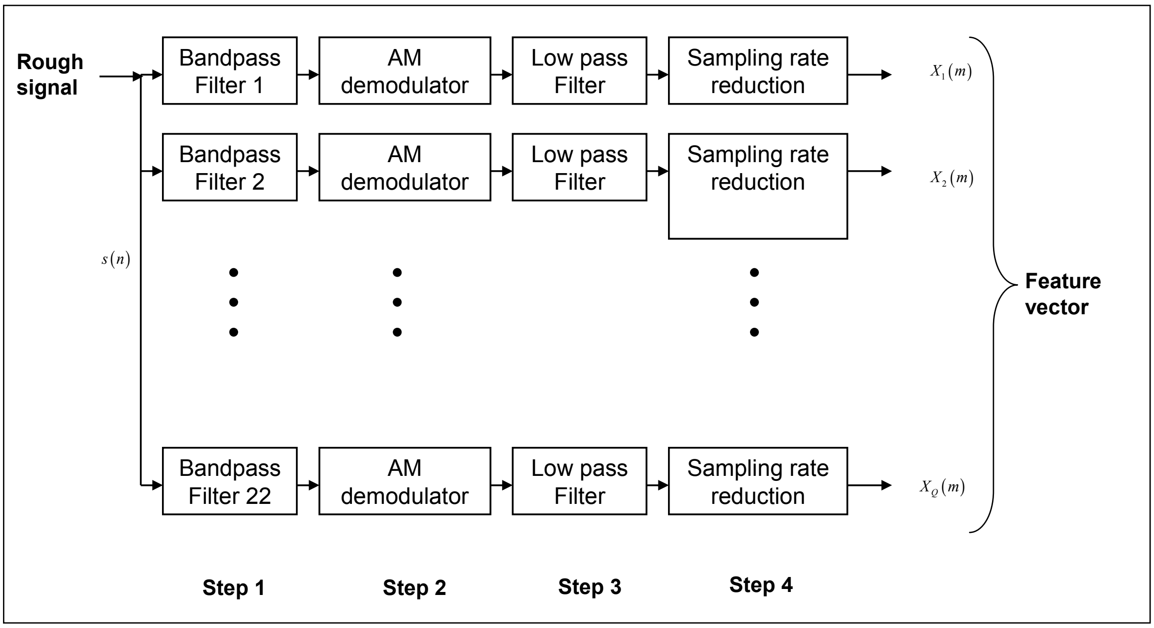

Figure 1: The 4 signal analysis steps: from rough sound samples $s(n)$ to the feature vector.

Step 1: Band pass filter

In [1, 2, 3 and 4], the relevance of the spectral content towards the automated cough identification is shown. To calculate this spectral content of the rough sound signal $s(n)$, a number of band pass filter blocks are applied. In a so called filter bank approach the total sound signal is divided into separate frequency ranges by using filter blocks. So each filter block covers a part of the total spectrum of the signal.

Step2: AM demodulator

The effect of the AM demodulation is illustrated on a signal coming from filter bank number 19, shown in figure 2. It is clear that the AM demodulated signal follows the instantaneous amplitude of the band pass filtered signal. Applying this AM demodulation to the total set of 22 band pass filters will give a vector with a dimension of 1 x 22, $\left[X_1(m) \quad X_2(m) \quad \dots \quad X_{22}(m)\right]^T$ called the feature vector.

Steps 3 and 4: Low pass filtering and sample rate reduction

To reduce the huge information rate the feature vectors will be sub sampled. Here, a third order low pass Butterworth filter is applied, with a cut off frequency set to 100 Hz.

Classification

Each sound is compared to a training set of feature vector sequences, by means of the dynamic time warping (DTW) algorithm as described in [6] and [7]. The different duration of the cough sounds results in a 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 sequence (series of feature vectors) and the other one as a reference sequence. Taking vector by vector of the test sound template, the DTW algorithm looks for the vector-path in the training template that results in the minimal distortion. Once the vector-path of minimal distortion is found, a figure can be calculated to express the similarity between test and training sequence.

Results and discussion

Since the number of online registered sound files is limited (44), all sound files are manually listened and visually inspected to validate the sound classification algorithm. This manual listening resulted in a labeled database for all the 592 sounds, tagging the individual sound with either the label ‘cough’ (159 sounds or 27%) or the label ‘other’ (433 sounds or 73%).

Recognition performance is assessed applying the ‘leave 10 out’ method. The classifier is trained, using all the individual cough events, except 10%. The remaining 10% is used for testing. With this 10% of the cough sounds, 10% of the ‘other’ sounds are mixed, to have a representative snap check. A permutation is applied 10 times, until all cough sounds have been in the test class. The recognition performance is summarized in table 1.

The number of misclassifications in the case of cough sounds is 23 out of 159 coughs, or 14.5%. In the case of other sounds, there is a misclassification of 13,4%. The total accuracy of the sound recognition in field conditions is 86.2%. Comparing this type of cough recognition with other experiments where the coughs were induced using citric acid there is a 8% lower recognition rate [1,8]. The main reason for this lower rate is the fact that the experiments where held in field conditions, where ambient noise might add a disturbance factor in the sound signals, whereas in [9] the experiments were held in laboratory circumstances.

Using neural networks to classify different sounds a performance of 94.8% was obtained for correct classification of pig coughs in laboratory circumstances. Here as well there is a higher recognition rate than in the results stated above, but again a reason may be the fact that the tests were not disturbed by ambient noise.

Table 1: The recognition performance of the introduced algorithm. The total correct recognition is 511 out of 593 sounds or 86.2 %.

Set	**Cough sounds**			**Other sounds**			**Total**		
	Total number	**Correct classified**	**%**	**Total number**	**Correct classified**	**%**	**Total number**	**Correct**	**%**
1	16	15	93.7	43	41	95.3	59	56	94.9
2	16	13	81.2	43	35	81.4	59	48	81.4
3	16	14	87.5	44	39	88.6	60	53	88.3
4	16	14	87.5	43	36	83.7	59	50	84.7
5	16	15	93.7	43	40	93	59	55	93.2
6	16	12	75	44	41	93.2	60	53	88.3
7	16	15	93.7	43	30	67.8	59	45	76.3
8	16	14	87.5	43	35	81.3	59	49	83
9	16	13	81.2	44	40	90.9	60	53	88.3
10	15	11	73.3	43	38	88.3	58	49	84.5
Total:	159	136	**85.5**	433	375	**86.6**	593	511	**86.2**

Conclusion

In this research it was investigated whether cheap microphones are able to register cough sounds in the field. These cough sounds are to be used as indicator for an early warning system for pig epidemics. Using a simple algorithm and by applying on-line monitoring of continues sound registration, it was possible to detect different cough events in field conditions with an accuracy of 86.2%. Although this classification performance is slightly lower than experiments under laboratory conditions - due to environmental noise - it can be used as an indicator for diseases in swine stables.

References

[1] 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

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

[3] 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

[4] V. Hirtum, A. and Berckmans D., "Automated recognition of spontaneous versus voluntary cough", Medical engineering & physics, vol. 24, pp. 541-545, 2002

[5] Maragos, P., Kaiser, J. F., and Quatieri, T. F. "Energy separation in signal modulations with application to speech analysis" IEEE Trans. On signal Processing, Vol. 41, No. 10, 3024-301, Oct 1993.

[6] Deller J., Proakis J., Hansen J., Discrete-time processing of speech signals, (1993), Prentice Hall NewJersey.

[7] Rabiner L., Juang B., Fundamentals of speech recognition (1993), Prentice Hall, New Jersey.

[8] A. V. Hirtum and D. Berckmans, "Objective recognition of cough-sound as biomarker for aerial pollutants," International Journal of Indoor Air Quality and Health 14(1):10-5, 2004 Feb.

[9] D. Moshou , A. Chedad ,A.V. Hirtum , et al., An intelligent alarm for early detection of swine epidemics based on neural networks (vol 44, pg 167, 2001) Transactions of the ASAE 44 (2): 457-457 Mar-Apr 2001