EVALUATION OF AN ALGORITHM FOR COUGH DETECTION IN PIG HOUSES

Jans P.[1], Guarino M.[2], Costa A.[2], Aerts J.-M.[1], Berckmans D.[1]

[1]Department of Agro-engineering and -economics, Katholieke Universiteit Leuven,
Kasteelpark Arenberg 30, B-3001 Leuven, Belgium,
e-mail: daniel.berckmans@agr.kuleuven.ac.be.
[2]Department of Veterinary and Technological Sciences for Food safety,
Faculty of Veterinary Medicine, via Celoria, 10, 20133 Milan, Italy.

Abstract: 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 algorithm was tested in field conditions. Pig cough sounds were registered on 44, 150 days old, 60 kg heavy Landrace x Large White x Duroc crosses, by an operator holding a microphone at about 20 to 50 cm from the pigs head. From these sound files, feature vectors were extracted, containing information on the sound energy, spectral properties and time derivates. These feature vectors were compared to a reference set by means of a dynamic time warping algorithm. This leads to a two class classification: ill, no ill. The classification was checked by a veterinarian and found to be correct in 86 % of the cases.

Keywords: diagnosis, filter banks, biocybernetics, biomedical systems, modelling.

1. INTRODUCTION

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 (Tothill, 2001). 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 Moshou et al. (2001) and Van Hirtum and Berckmans (2003a, 2004) 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 Urbain et al. (1996) and Van Hirtum and Berckmans (2003a), 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.

The objective of this study was to develop and test a cough recognition algorithm that can be used in pig houses under field conditions.

2. MATERIALS AND METHODS

2.1. Animals and housing

Experimental data were obtained from swine houses for finishing pigs assigned to the Parma ham production in Northern Italy. The pigs (Landrace x Large White x Duroc crosses for Parma ham production) were in the first period of the finishing phase. Their mean weight was around 60 kg and their mean age was 150 days. The farm was composed of three barns for piglets, sows, and finishing pigs. The barn for finishing pigs was an open-space of 8.3 m x 83 m. It was subdivided in 16 boxes of 6 x 5 m wide, containing 50 pigs each. Each boxes had a dunging area of 1.3 m x 5 m. The boxes were delimited by a little wall in concrete, 1.0 m high and 0.2 m thick.

Sick pigs affected by cough, were confined in the six final boxes, in order to separate them from the healthy ones. A serological assay of blood samples to verify the presence of Pleuropneumonitis antibodies was conducted on sick pigs to verify the source of coughing. After the slaughtering, Pleuropneumonitis was confirmed by the autopsy examine performed by the farm veterinarian. The average daily gain (ADG) in healthy pigs was 653 g/day, while the sick pigs showed a lower ADG calculated in 437 g/day.

2.2. Measurements

Pig's 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, resulting in almost 4 hours of data. The details of the recordings are shown in table 1.

Table 1. Overview of the continuous registered sounds.

Number of on-line registered sound files	44 files
Duration	Min: 3.2 s
	Max: 23.2 s
	Average: 9.7 s
Number of individual sounds	592 sounds
Number of coughs	159 sounds (27 %)
Number of other sounds	433 sounds (73 %)

2.3. Sound signal analysis

The signal analysis was done in four steps. In these four steps a feature vector was created, that was used to classify the sound signal. The four signal analysis steps are schematically illustrated in figure 1.

Step 1: Band pass filter. In the work of Tothill (2001), Moshou et al. (2001), and Van Hirtum and Berckmans (2003a, 2004), 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 were applied. Each filter block covers a part of the total spectrum of the signal. In this case third order Butterworth filters were used to implement a total of 22 filter blocks. The filter bank approach in this research is less calculation power consuming than the application of the more standard Fourier transform that was used by Van Hirtum and Berckmans (2002, 2003a, 2004). Another advantage of this approach is that one only needs to evaluate the filters that are necessary to discriminate the desired sounds (cough sounds in this case) from the others. Psychophysical studies have shown that the human perception of the frequency content of sounds does not follow a linear scale. To meet this non linear subjective sound perception, the lower frequencies were divided into smaller pieces (22 smaller bandwidths). The highest upper cut-off frequency was 9500 Hz, because the sampling rate of the recording was 22050 Hz.

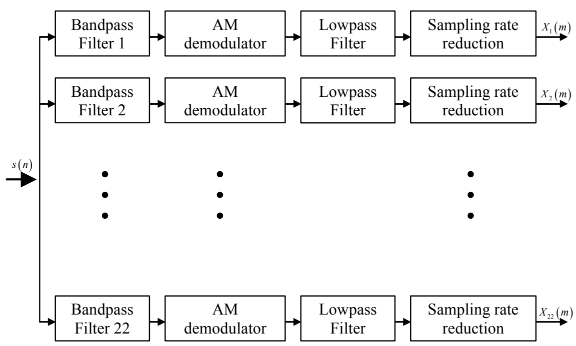

Fig. 1. The 4 signal analysis steps: from rough sound samples $s(n)$ to the feature vector: $[X_1(m)\ X_2(m)\ \ldots\ X_{22}(m)]^T$

Step 2: AM demodulator. The starting point of AM-FM demodulation is that any sound can be modelled with an Amplitude Modulation – Frequency Modulation (AM-FM) model. By band pass filtering, a small bandwidth can be isolated and modelled by an exponentially damped AM-FM signal. In this work, only the AM component was further used to make the discrimination between different sounds. The AM-FM model for the signal coming from the first band pass filter block $s_1(n)$ can be written as:

$$s_1(n) = a(n)\cos\left(\Omega_c n + \Omega_m \int_0^n q(m)\,dm + \theta\right) \quad (1)$$

Where Ω_c is the carrier frequency, $|q(n)|\leq 1$ is the frequency information signal, Ω_m is the maximum frequency deviation from Ω_c ($0<\Omega_m<\Omega_c$) and $\theta = \phi(0)$ is an arbitrary phase offset. Obviously, this model was applied to all the 22 band pass filter blocks.

The above model can be efficiently worked out by means of the Teager energy operator (TEO). The discrete time Teager energy operator (TEO) is defined as follows (Cairns et al., 1996):

$$\Psi_d\left[s(n)\right] = \frac{s^2(n) - s(n-1)s(n+1)}{T^2} \quad (2)$$

Where T is the sampling period. From this the AM component, $|a(n)|$, is calculated as:

$$|a(n)| \approx \sqrt{\frac{\Psi\left[s(n)\right]}{1-\left(1-\dfrac{\Psi\left[t(n)\right]+\Psi\left[t(n+1)\right]}{4\Psi\left[s(n)\right]}\right)^2}} \quad (3)$$

where $t(n) = s(n)-s(n-1)$.

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 gives a vector with a dimension of 1 x 22, $[X_1(m)\ X_2(m)\ \ldots\ X_{22}(m)]^T$. Further, this vector will be called the feature vector. The AM demodulated signal was calculated at the same sampling rate as the original signal (22050 Hz) and as a result a feature vector could be put together every 1/22050=45.3μs. As this is too much information for the classification algorithm to master, a reduction of the sample rate was inevitable.

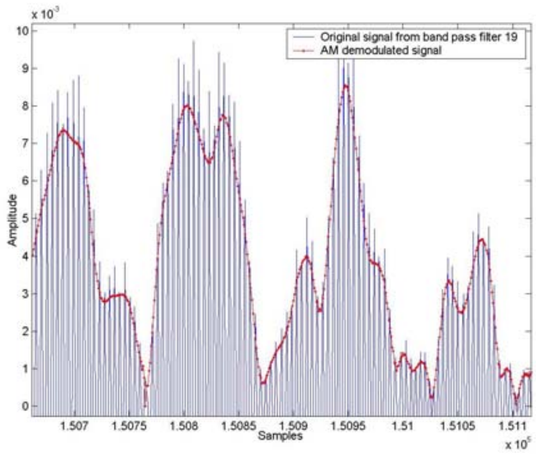

Fig. 2. AM demodulation of a sound fragment coming from band pass filter number 19.

Steps 3 and 4: Low pass filtering and sample rate reduction. To reduce the huge information rate (22 values in the feature vector, every 45.3 μs), feature vectors were left out. In this case, for every block of 220 feature vectors, the first feature vector was kept and the other 219 vectors were omitted (Step 4). To execute this sub sampling step in conformance with the Nyquist theorem, some low pass filtering was done. Here, a third order low pass Butterworth filter was applied, with a cut-off frequency set to 100 Hz (Step 3). The result of the applied scheme as shown in figure 1, is a feature vector with 22 values, at a sample rate of 22050/220 ≈ 100Hz. This gives one feature vector, every 10 ms.

2.4. Classification

Cough sound recognition was assessed with dynamic programming i.e. dynamic time warping (DTW) (Deller et al., 1993; Rabiner and Juang, 1993). As indicated higher, each sound was divided into frames of equal length and the features of each frame were stored in a feature vector. Thus, each sound was represented by a sequence of data feature vectors that form a sound template. During the recognition phase the template of the test sound is compared to each template in the set of training templates using the DTW algorithm. The training template producing the minimum distortion determines the classification output. For more detailed information the reader is referred to Van Hirtum and Berckmans (2002).

3. RESULTS AND DISCUSSION

In Figure 3, an example is shown of an original sound recording for a continuous sound registration of 19.2 s. In this example file, a total of 19 cough sounds was automatically detected. This number coincides with the manual, auditory detected number of coughs.

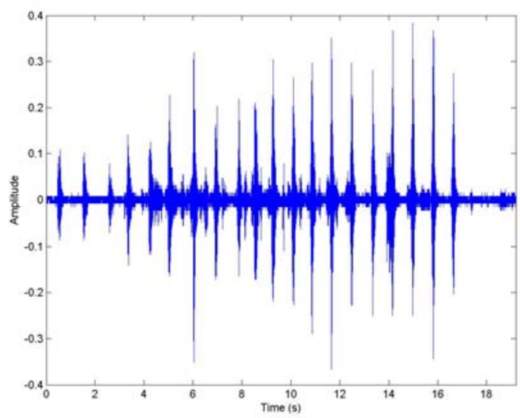

Fig. 3. The original 19.2 s continuous sound registration. In this registration 19 cough sounds were identified.

Since the number of online registered sound files is limited (44), as shown in table 1, all sound files were manually listened and visually inspected to validate the sound classification algorithm. This manual listening resulted in a labelled 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 was assessed applying the well known 'leave 10 out' method. The classifier was trained, using all the individual cough events, except 10 %. The remaining 10 % was used for testing. With this 10 % of the cough sounds, 10 % of the 'other' sounds were mixed, to have a representative snap check. A permutation was applied 10 times, until all cough sound had been in the test class. This method is known to provide a good estimation of the error in case of small databases. The recognition performance of the newly developed algorithm applied on the 44 sound files is summarized in Table 2.

Table 2. The recognition performance of the cough detection algorithm on field data.

Set	Cough sounds correctly classified (%)	Other sounds correctly classified (%)
1	93.7	95.3
2	81.2	81.4
3	87.5	88.6
4	87.5	83.7
5	93.7	93.0
6	75.0	93.2
7	93.7	67.8
8	87.5	81.3
9	81.2	90.9
10	73.3	88.3
Average	85.5	86.6

The accuracy of the cough recognition with the features and classification approach described higher yielded on average 86%. Depending on the test set, the recognition performance reached values between 73% and 94%. This is on average 8% lower than the recognition rate obtained in case of citric acid induced coughing (Moshou et al., 2001; Van Hirtum and Berckmans, 2003a; 2004). Several factors contributed to the lower recognition rate. Firstly the data were registered in field conditions and not in a laboratory set-up as was the case in previous work. Secondly, in contrast to the results presented in previous work, individual sounds were objectively and automated detected from the continuous and on-line sound registrations. For application in the field, the average success rate of 86% for detection of individual coughs seems acceptable because it can be expected that ill animals will cough several times and the chance that they will be detected is (much) higher than 86%.

4. CONCLUSIONS

In this research, it was demonstrated that the combination of on-line measured sound information by means of a cheap microphone with a cough sound recognition algorithm, can be used to monitor the health status of pigs in field conditions. The cough recognition algorithm was tested on 44 sound files recorded in field conditions. Cough could be classified successfully with an accuracy of 86%.

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