Frequency analysis for real-time recognition of sick pigs and disease monitoring in pig houses*

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Abstract

This paper extends existing cough identification methods and proposes a real-time version for identifying sick pig cough sounds. The analysis and classification is based on the frequency domain characteristics of the signal, while an improved procedure to extract the reference is presented. This technique evaluates fuzzy c-means clustering to parts of the training signals that mirror the cough characteristics. The identification process can be implemented for real-time applications that would improve and speed up the treatment procedure in pig houses.

Keywords: Real-time recognition, Cough analysis, Spectral analysis, Signal processing

Introduction

Cough is a sudden air explosion from the airways followed by a characteristic sound (Korpáš *et al*., 1996). Being one of the body's defence mechanisms against respiratory infections, it can be a sign of disorder or infection of the respiratory system. It has been used as an index for over 100 diseases and an experienced physician can identify an infection based on the cough sound. This fact has led researchers to further study cough recording and analysis methods (e.g. Subburaj *et al*., 1996) and to develop automated identification techniques (e.g. Matos *et al*., 2006).

The importance of coughing as a means of prognosis does not refer only to humans, but also to animals. It has been shown that pig vocalisation is directly related to pain and a classification of such sounds has been attempted in (Marx *et al*., 2003). Furthermore, it is common practice in small pig houses to assess cough sounds for diagnostic purposes. This approach however cannot be applied in large pig houses with many animals and a possibly harmful environment. Therefore there have been attempts to identify the characteristics of coughing in animals (Van Hirtum & Berckmans, 2001 and Moreaux *et al*., 1999) or correlate the cough characteristics with ae-

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rial pollutants (Van Hirtum & Berckmans, 2004) and even to automatically identify cough sounds from field recordings (Van Hirtum & Berckmans, 2003a, 2003b).

To further extend the above results, the present paper proposes a *real-time* method of sick pig cough identification. In a real-time application, common techniques such as preprocessing of the whole signal or normalisation are not available. The amplitude of the signal for detection of acoustic events is also not an adequate criterion due to the variable distance of the animals from the microphones used. The frequency content of the acquired signal is therefore the main characteristic that can be evaluated. It is shown that although the frequency content of a sick cough signal is not particularly different from other pig sounds, such as screams or sneezes, it can be used for identification purposes by carefully selecting the training set for the algorithm and the similarity criteria. Successful application of the proposed technique could result in early identification of an infected animal and prevent a disease from spreading.

Section 2 describes the sound acquiring process, the proposed algorithm and some background mathematical techniques. The simulation results and the discussion are presented in section 3, followed by the conclusions in section 4.

Material and methods

Experimental data

The data, both pathologic and healthy coughs, used for the analysis are cough sounds recorded in laboratory conditions. The healthy coughs were induced in an inhalation chamber by injecting an irritating substance namely 0.8 moles per litre of citric acid dissolved in a saline solution (0.9% NaCl) (see Van Hirtum & Berckmans, 2003b for more information on the installation environment data acquisition process). The nebulisation of citric acid stimulates the cough receptors directly resulting in coughing. In total, 11 experiments were conducted to 3 male and 3 female healthy Belgian Landrace piglets of $9-12$ weeks of age and $20-40$ kg of weight. The experiments were conduced in each individual animal.

In order to record pathologic coughs, the piglets were anaesthetised with azaperone (4 mg/kg IM[†]), ketamin (10 mg/kg IM) and thiopental (10 mg/kg IV[‡]). They were treated (by intratracheal administration) with lipopolysaccharide from *Escherichia coli* diluted in sterile saline ($100\ \mu$g/kg). A non-toxic strain of *Pasteurella multocida* (code 3301) was used to generate bronchopneumonia, a common respiratory infection in piglets (Kobis & Friis, 1996).

Apart from the cough sounds, other sounds (such as screams, sneezes or metal sounds) were acquired and labelled accordingly by auditory processing. Therefore, the generated data set includes individual sounds of 231 *healthy* coughs, 291 *sick* coughs, 18 *screams*, 19 *sneezes*, 31 *grunts* and 81 *metal* sounds.

[†] intramuscular
[‡] into a vein

The acoustical data are recorded with a sampling frequency of 22050Hz using a unidirectional electret microphone (U.S. Blaster, $20\text{Hz} - 20\text{kHz}$ frequency response) and a sound card (SoundBlaster, 16 bit).

Signal analysis

The frequency characteristics of the signal on which the identification process is based, is the Power Spectral Density (PSD). In Figure 1, for example, the PSD of three different pig sounds, namely a *sick* cough, a *grunt* and a *scream* are presented. It is clear that the *grunt* has considerably different frequency content than the others with the energy being concentrated below 2kHz. However, the frequency content differences between the *scream* and the *sick* cough are not so apparent. Although it could be argued that the presence of higher frequency harmonics in the *scream* signals could be used as a guide for classification, their exact frequency is highly dependent on the animal making it an unsatisfactory criterion. Therefore, the selection of the reference and the similarity criteria need to be selected by taking into account that the same sounds from different animals result in different frequency content.

Definition of the reference

This section presents the procedure followed to define a reference PSD vector. Although not presented in Figure 1, other sounds have similar frequency characteristics as a *sick* cough. However, experimentation suggested that only scream and sick cough sounds should be used in training the algorithm (defined in section *fuzzy c-means clustering*).

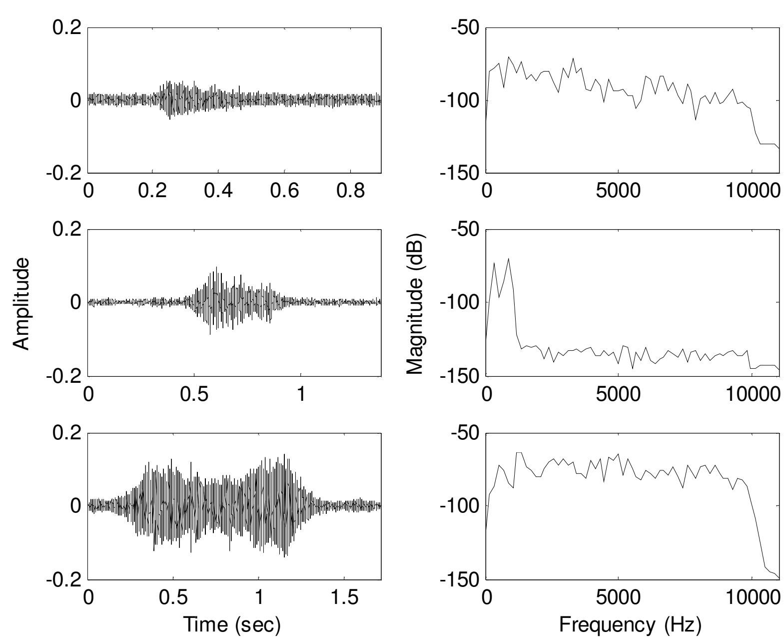

Figure 1: Time-signal (left column) and frequency content (right column) for a sick cough (top row), a grunt (middle row) and a scream (bottom row)

Power Spectral Density of the training set

To define a reference, ten sick cough signals with average duration $\mathrm{t_c} = 834\ \mathrm{ms}$ and five scream signals with average duration $\mathrm{t_s} = 1.91\mathrm{s}$ were used. Each signal was split into parts of length $\mathrm{t_w} = 200\ \mathrm{ms}$ (or $\mathrm{N_w} = 4410$ samples) with a 50% overlap to each other allowing for the high energy parts of each signal to be extracted from the silence before and after the signal (depicted in the left column of Figure 1). Experimentation suggested that only the parts of the signal that had a total energy exceeding 40% of the part with the maximum energy be used, and the frequency content of each was extracted, as described in the next section. This procedure is summarised in Algorithm 1. To deal with noisy signals or signals with low amplitude, the mean value of each PSD vector is subtracted resulting in values fluctuating around zero.

Algorithm 1: Extraction of high energy parts of a signal

for every signal $s(k)$ **do**
  Split $s(k)$ into $s_p(k)$ of duration t_c with overlap t_{ov}
  Find $s_{p,\max E}(k)$ with the maximum energy $E_{\max}$
  for every $s_p(k)$ **do**
    if $Energy\left\{s_p(k)\right\} \geq 0.4E_{\max}$
      then $\mathbf{PSD} := \left[\mathbf{PSD} \quad \mathbf{PSD}_{s_p(k)}\right]$
  return PSD

Extraction of signal characteristics

In this work, the Discrete Fourier Transform (DFT) that is widely used in signal processing (Oppenheim *et al.*, 1999), is used to extract the spectrum of the signals. For completeness, its main properties are described below.

Consider a discrete signal $s(k)$, $k = 0,1,\ldots,N-1$ sampled at frequency f_s. The N-point DFT of this signal is defined as

$$S_n = F\left\{s_k\right\}(n) \equiv \sum_{k=0}^{N-1} s(k) e^{-2\pi ink/N}, \ n = 0,1,\ldots,N-1 \tag{1}$$

where i is the imaginary unit and S_n is in general a complex number. The DFT reveals the frequency content of the sampled signal up to the Nyquist frequency $f_s/2$.

For this application, $N = 128$ (as in Van Hirtum & Berckmans, 2003b) is used leading to a frequency resolution of $f_r = 172Hz$, i.e. the frequencies at which the DFT was calculated were $F = kf_r$, $k = 1,2,\ldots,N/2+1$, which is common in animal speech processing.

Fuzzy c-means clustering

A fuzzy c-means clustering algorithm (Bezdek, 1981) is evaluated to form 2 clusters, namely the *sick* cough and the *scream* cluster. The centre of the *sick* cough cluster will later be used as a reference for the identification process.

Fuzzy c-means is a clustering method by which each point belongs to a cluster on a certain degree that is determined by its membership function (MF). Consider, for example, N d-dimensional vectors that need to be separated into c clusters. The classification process is based on the minimisation of

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m \left\| x_i - c_j \right\|^2 \tag{2}$$

where $m \leq 1$, c_j is the centre of the jth cluster, u_{ij} is the MF of vector i in cluster j and $\|\cdot\|$ any norm. Partitioning is then carried out by iterative optimisation of Eqn. (2) and the MFs and the centres of the clusters are updated using the following formulas

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{3}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{m} u_{ij}^m} \tag{4}$$

In this particular application, m was chosen to be 2; N was 47 after the extraction of the PSD vectors described in section *Power Spectral Density of the training set*; the Euclidean norm was chosen to describe the dissimilarity between the training vectors and the centre of the cluster; and $c = 2$, which refers to a *sick* cough and a *scream* cluster.

The result of the reference extraction and the fuzzy 2-means clustering is presented in Figure 2. By visual inspection it is clear that the PSD vectors of the *sick* cough signals are around the centre of the *sick* cluster, while the *scream* cluster is considerably different (except from the $6 - 8kHz$ frequency band).

Sound classification

The similarity criterion evaluated in the decision process is the squared Euclidean distance defined in (5).

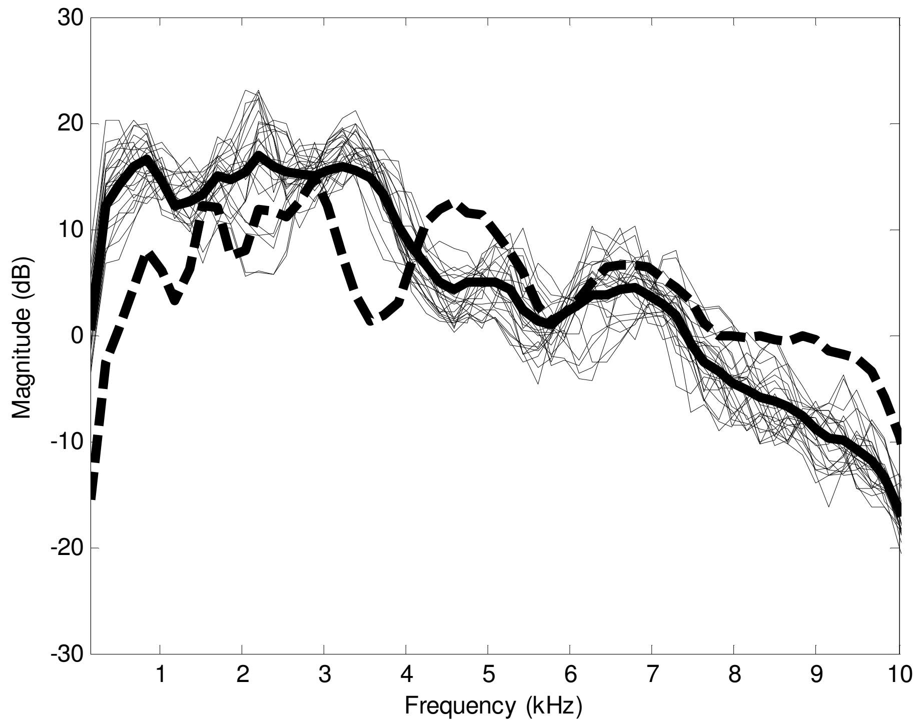

Figure 2: Normalised frequency content of the *sick* training set (thin lines), the centre of the *sick* (thick solid line) and *scream* (thick dashed line) clusters

$$d_e = \sum_{i=1}^{d} \left(\mathbf{PSD} - \mathbf{PSD_{ref}} \right)^2 \quad (5)$$

To further enhance the performance of the algorithm, the initial frequency range of $100-10000Hz$ was split into 9 frequency ranges as suggested by (Van Hirtum & Berckmans, 2003b). The mean and minimum squared Euclidean distance of the training set from the reference, along with the frequency ranges is presented in Table 1. Based on these values, the threshold distance in every band was manually chosen by inspection assuring a clear differentiation between the *sick* cough and the *scream* sounds. Every sound, whose frequency content is below the threshold would be characterised as *sick* cough. As is suggested by Table 1, only 5 frequency bands were eventually used. In the frequency ranges that the threshold value is marked as -, the signals were not easily distinguishable and were not used in the identification process.

Real-time Identification

The identification procedure comprises three main parts, namely the preprocessing of the signal as it is acquired, the extraction of the characteristics of the signal, and the comparison to the reference, as depicted in Figure 3.

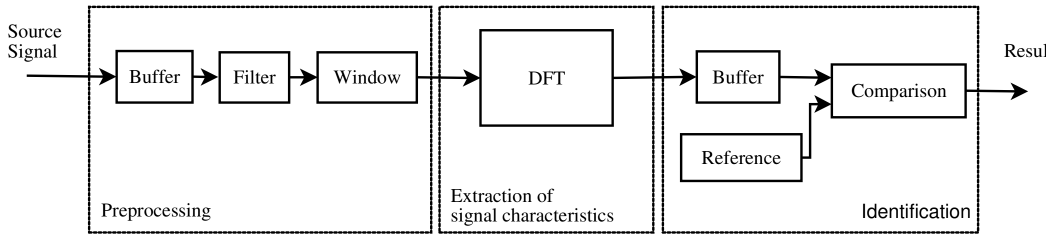

Figure 3: Flow chart of the identification procedure

Preprocessing

The input signal is split into small signal frames that can be processed the moment they are acquired. Each frame consists of $N = 128$ samples to comply with the size of the Discrete Fourier Transform as described in *Extraction of signal characteristics*}. Each frame is then preprocessed according to the following

1. Filtering
2. Windowing

Low frequency noise (e.g. ventilation) is present in most stable environments. Furthermore it has been shown (Van Hirtum & Berckmans, 2003a and references therein) that pig sounds have dominant frequencies below $10\,\text{kHz}$. Therefore a 10^{th} order Butterworth filter with pass band $100-10000Hz$ was applied.

As is common practice in signal processing (Oppenheim *et al*., 1999), to reduce edge effects and spectral leakage each frame was passed through an N-point Hanning window, whose amplitude is given by the following equation:

$$w(n) = 0.5\left(1-\cos\left(\frac{2\pi n}{N-1}\right)\right),\ n = 0,1,\ldots,N-1 \tag{6}$$

Table 1: Squared Euclidean distance of the training set in every frequency band and the threshold chosen

Frequency range (Hz)	Mean (minimum) distance		Threshold distance
	Scream sounds	Sick coughs	
100-1000	1088 (878)	711 (469)	750
100-6000	745 (461)	356 (244)	450
6000-10000	196 (51)	260 (73)	-
100-2000	87 (39)	82 (50)	-
2000-5000	511 (255)	183 (119)	200
2000-4000	372 (148)	65 (14)	150
4000-6000	20 (14)	40 (27)	-
2300-3200	62 (25)	26 (5)	40
7000-9000	57 (26)	91 (20)	-

Identification

The N=128 samples that were used by the DFT block belong to 6ms of the signal. Of course this cannot fully reflect the characteristics of the sound this frame belongs to. After the calculation of the DFT, $N_f = 33$ PSD vectors are buffered, equivalent to $t_{fr} = 200ms$ with an overlap of 25 PSDs (or $150ms$), and their mean value is obtained. This way the PSD of a whole sound was obtained (the 'whole sound' means the expected duration of a cough). Then the squared Euclidean distance from the reference is calculated for every frequency band as described in section *sound classification*. The part of the signal is identified as cough if its distance from the reference is below the assigned threshold in 2 or more frequency bands.

Results and Discussion

Each individual sound is processed using the proposed algorithm and is either identified as *sick* cough or not. Table 2 presents the total number of each sound and the number of them identified as *sick* cough when running the algorithm for a total of 656 sounds. False alarms (FAs) are obtained when sounds of other nature (such as metal sounds or sneezes for example) are identified as cough. Since *sick* coughs occur in cough arrays, they are repeated, so it is of greater importance to correctly identify a *sick* cough than to identify every cough in the pig house. Therefore reduction of FAs is considered a priority in this paper (although the correct identification of *sick* coughs is also taken into consideration). FAs can be kept to a minimum by changing the number of frequency bands in which a signal needs to meet the identification criteria, but experimentation suggested that with this specific algorithm and fixed threshold distances, the percentage of FAs in the identified sounds is almost constant at about 13%.

An overall performance of 87% of correctly identified sounds was achieved and about 82% of the *sick* coughs were identified. This level of performance indicates that the algorithm could be applied in practice with a minimum number of false alarms. Furthermore, the percentage of sick cough identification can be increased (by decreasing the number of regions that a signal needs to be *close* to a cough signal) by having a practically constant FA to correct identification ratio.

The real-time nature of the proposed algorithm makes it an attractive solution to cases where immediate action is necessary. This is the case in big pig houses where a disease can spread very fast and reliable identification is vital for the smooth functionality of the pig house.

The solutions to cough identification or classification previously presented in the literature (e.g. Matos *et al.*, 2006 and Van Hirtum & Berckmans, 2003b), have considered the whole sound or a complete recording to be available for processing.

By contrast, the approach described here is a modification to the approach of (Van Hirtum and Berckmans, 2003b) that allows it to be implemented in real-time. Although the identification results of (Van Hirtum and Berckmans, 2003b, 2004) are superior to the ones presented here with a positive recognition rate of 95%, their global identification rate of 85% is not better, while they require a bigger training set (twice the size of the one used in this paper) and cannot be directly applied in a real-time application. Furthermore, the results of (Matos *et al.*, 2006) that evaluate Hidden Markov Models to sound recordings and obtain a detection rate of 82%, don't seem to be superior to the ones in the present paper and are still not implementable in real-time. However, the results are not directly comparable since the implementation of (Matos *et al.*, 2006) refers to human cough sounds.

Although the detection of cough sounds is important, this paper considers the case of *sick* coughs because they point to a spreading disease, hence they need to be immediately identified and have their significance evaluated. It is suggested that there is a substantial difference between the spectrograms of *healthy* and *sick* cough sounds that have enabled the algorithm to extract only *sick* coughs from a given set. It should also be stressed out that although the algorithm was tested in individual sounds, it can be fully applied in continuous recordings.

Table 2: Identification results of the proposed algorithm

Sound	Number of sounds	Number of sounds identified as cough	Percentage (%)
Healthy cough	231	31	13.4
Sick Cough	281	231	82.2
Scream	13	1	7.6
Sneeze	19	2	10.5
Grunt	31	2	6.4
Metal	81	9	11.1

Conclusions

This paper proposed a real-time algorithm for online identification of sick pig cough sounds. The extracted sounds can be evaluated by a human operator, speeding up the decision process in cases where action needs to be taken. False alarms (section *Results and discussion*) are kept to a minimum leading to decreased work load and decreased unnecessary action. The real-time applicability of the algorithm can be a first step towards localisation of sick animals in a big pig house and provide enhanced treatment of diseases.

The method used to assess the different kinds of sound is the Discrete Fourier Transform, which revealed the frequency content of each sound. The existence of fast algorithms for its implementation makes it an attractive tool for real-time applications. It was further shown that, although the spectrogram of sick coughs is not particularly different from other sounds occurring in a stable, they can nonetheless be separated by careful selection of the reference and the threshold to be used. The results suggest that with proper training, the majority of sounds identified are indeed sick coughs and false alarms are kept to a minimum.

Since the cough characteristics vary considerably due to environmental changes, further work should be towards the direction of robustness and adaptability of the algorithm in different conditions.

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References

Bezdek, J.C. 1981. *Pattern recognition with fuzzy objective function algorithms*. Plenum Press, New York.

Kobisch, M., and Friis, N.F. 1996. Swine mycoplasmoses. *Revue Scientifique et Technique De L' Office International des Epizooties* **15**(4) 1569-1605.

Korpáš, J., Sadloňová, J., and Vrabec, M. 1996. Analysis of the cough sound: An overview. *Pulmonary Pharmacology* **9**(5-6) 261-268.

Marx, G., Horn, T., Thielebein, J., Knubel, B., and von Borell, E. 2003. Analysis of pain-related vocalization in young pigs. *Journal of Sound and Vibration* **266**(3) 687-398.

Matos, S., Birring, S.S., Pavord I.D., and Evans, D.H. 2006. Detection of cough signals in continuous audio recordings using hidden markov models. *IEEE Transactions on Biomedical Engineering* **53**(6) 1078-1083.

Moreaux, B., Beerens, D., and Gustin, P. 1999. Development of a cough induction test in pigs: effects of SR 48968 and enalapril. *Journal of Veterinary Pharmacology and Therapeutics* **22**(6) 387-389.

Oppenheim, A.V., Shafer, R.W., and Book, J.R. 1999. *Discrete-time signal processing*. Upper Saddle River, N.J.: Prentice Hall.

Subburaj, S., Parvez, L., and Rajagopalan, T.G. 1996. Methods of recording and analysing cough sounds. *Pulmonary Pharmacology* **9**(5-6) 269-279.

Van Hirtum, A., and Berckmans, D. 2001. The fundamental frequency of cough by autocorrelation analysis. In: *Proc. EUROSPEECH: 7th European Conference on Speech Communication and Technology* Aalborg, Denmark, 2435-2438.

Van Hirtum, A., and Berckmans, D. 2003a. Considering the influence of artificial environmental noise to study cough time-frequency features. *Journal of Sound and Vibration* **266**(3) 667-675.

Van Hirtum, A., and Berckmans, D. 2003b. Fuzzy approach for improved recognition of citric acid induced piglet coughing from continuous registration. *Journal of Sound and Vibration* **266**(3) 677-686.

Van Hirtum, A., and Berckmans, D. 2004. Objective recognition of cough as biomarker for aerial pollutants. *Indoor Air* **14**(1) 10-15.