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Fuzzy approach for improved recognition of citric acid induced piglet coughing from continuous registration

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Abstract

A natural acoustic indicator of animal welfare is the appearance (or absence) of coughing in the animal habitat. A sound-database of 5319 individual sounds including 2034 coughs was collected on six healthy piglets containing both animal vocalizations and background noises. Each of the test animals was repeatedly placed in a laboratory installation where coughing was induced by nebulization of citric acid. A two-class classification into 'cough' or 'other' was performed by the application of a distance function to a fast Fourier spectral sound analysis. This resulted in a positive cough recognition of 92%. For the whole sound-database however there was a misclassification of 21%. As spectral information up to 10000 Hz is available, an improved overall classification on the same database is obtained by applying the distance function to nine frequency ranges and combining the achieved distance-values in fuzzy rules. For each frequency range clustering threshold is determined by fuzzy *c*-means clustering.

1. Introduction

The occurrence of coughing in piglets is shown to depend on air velocity and temperature during transport and on housing conditions [1]. Effects of environmental variables such as aerial ammonia and dust concentration on the respiratory tract system are observed [2,3].

The amount of coughing and the frequency of occurrence is noted by experienced herdsmen or pig farmers as a natural alarm. Close human attention however is not evident due to the great number of animals in a possible harmful environment and the need for continuous observation

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[4]. So in general health control would benefit from automated, contactless and on-line cough observation.

In the literature some contactless on-line cough recognizers are presented for both human and pig. An on-line cough counter for use as a diagnostic tool in piggeries was developed based on a fixed template shape of the amplitude of a cough-signal in the time-domain, after the signal was split into eight frequency channels [5]. However, this approach includes some inaccuracies since other sounds may fit the template. Speech processing was performed on some pig vocalizations, including 15 records of coughing from slaughter pigs, for the detection of stress [6]. Analysis was conducted on the number of formants within the LPC-spectrum. For coughing this resulted in a 87% recognition. A 4-class hybrid neural network approach presented in Ref. [7] resulted in a correct cough recognition of 94%.

A very accurate and continuous, but non-contactless method for cough assessment in clinical and scientific settings involving humans is described in Ref. [8]. By applying a single amplitude-trigger to the high-pass filtered acoustical signal in combination with the detection of cough-induced fast movements of the body, recorded with a static charge-sensitive bed, sounds like talking are ignored. However in order to detect the mentioned body movements, the subject may not move and so it is not extendable towards an animal application. Other interactive, diagnostic cough analysis systems for humans make use of the signal features in the frequency domain to make a visual interpretation of individually registered cough-signals [9,10].

The research in this paper describes an algorithm for on-line contactless cough recognition out of a continuous sound registration based on an automated recognition of the acoustical signal features in both time- and frequency-domains.

2. Method

2.1. Experimental set-up

A first requirement to study the acoustical characteristics of cough-signals on animals, is the ability to *induce coughing* in a controlled way. Therefore a reproducible method to evoke a meaningful number of coughs in a restricted time-interval of 30 min has been developed for healthy individual Belgian Landrace piglets. The entire procedure, based on nebulization of an irritating substance inside a closed laboratory installation namely citric acid, is explained in detail in Ref. [11].

Each experiment consisted of 30 min continuous sound registration containing both coughing and a lot of superfluous background noises. Therefore, a first goal was the distinction of individual sounds out of background noise. Cough recognition was then assessed using signal analysis on the retrieved *individual* sounds.

Each of the individual sounds was *auditively* labelled as ‘cough’ or ‘other’. The auditive classification was used to evaluate the automated algorithm recognition.

2.2. Test installation, experiments and sound diversity

The *laboratory installation* used, described in Ref. [12], consisted of a metal construction, dimensions $2000 \times 800 \times 950$ mm ($l \times w \times h$), with a plastic cover. As environmental variables may act upon the respiratory tract and so upon the cough-signal [2,3], NH_3 concentration, dust concentration, air-flow rate and temperature inside the closed test installation were controlled. Experiments were carried out at room temperature and at an air-flow rate of $10\ m^3/h$. The ammonia concentration was less than 1 ppm. Dust particles of size greater than 1 μm were filtered out.

Sound acquisition was performed with a 16-bit digitalization sound card and a common PC. A unidirectional condenser microphone (Shure 16A) with a flat frequency response of 20 up to 20 000 Hz was positioned inside the laboratory installation through an aperture in the plastic cover. So, during all recordings the microphone was always between ± 0.4 and ± 1 m out of reach of the laboratory animal. Sample frequency was determined to be 22 050 Hz. Other recording parameters were 16 bit, mono.

Eleven *experiments* were carried out on six different healthy animals among which three were males and three females. Animal age and weight varied respectively between 9 and 13 weeks and 20 and 40 kg. Each experiment covered induction of coughing on one individual animal.

A whole gamut of registered *sounds* can be distinguished. Firstly there were animal vocalization sounds. Besides the intended cough sounds, this group consisted mostly of grunting and sounds due to respiration. A second sound group was caused by the followed experimental procedure. On the one hand the need for a test installation introduced metal noises due to animal movements inside the installation material. The cough-induction procedure on the other hand included some noise: e.g., the requested ventilation for nebulization. Finally there occurred background noises due to ventilation in the room containing the test installation, due to human presence (e.g., talking, shutting of doors), etc.

2.3. Time–frequency analysis

Time–frequency characteristics of each sound were determined by calculating the power spectral density (PSD) using the fast Fourier transform on the windowed time-signal. A Hanning window of size 128 sample values with no overlap was applied. The used window length of 128 (or 6 ms) in the time-domain corresponds to a frequency resolution of 170 Hz which is commonly used in animal-speech processing [13]. A sampling frequency of 22 050 Hz was used giving frequency information up to 10 000 Hz. So each sound was represented in the frequency domain by a PSD-vector containing 65 components.

2.4. Fuzzy c-means clustering

$\mathbf{X}$ is any finite set of n real p-dimensional input-feature vectors: $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\} \subset \mathbb{R}^p$; each $\mathbf{x}_k = (x_{k1}, x_{k2}, \dots, x_{kp}) \in \mathbb{R}^p$ is a feature or pattern vector; and x_{kj} is the jth feature or characteristic of observation $\mathbf{x}_k$; V_{cn} is the set of real $(c \times n)$ matrices; c an integer, $2 \leqslant c < n$. The set defined in the following equation is the *Fuzzy c-partition space for* $\mathbf{X}$.

$$M_{fc} = \left\{ \mathbf{U} \in V_{cn} \mid u_{ik} \in [0, 1]\ \forall i, k; \sum_{i=1}^{c} u_{ik} = 1\ \forall k; 0 < \sum_{k=1}^{n} u_{ik} < n\ \forall i \right\} \tag{1}$$

Row i of a matrix $\mathbf{U} \in M_{fc}$ exhibits values of the ith membership function (or the ith fuzzy subset) $\mathbf{u}_i$ in the fuzzy c-partition $\mathbf{U}$ of $\mathbf{X}$. Because each column sum is 1 (Eq. (1)), the *total* membership for each $\mathbf{x}_i$ in $\mathbf{X}$ is 1, but since $0 \leqslant u_{ik} \leqslant 1 \ \forall i, k$ it is possible for each x_k to have an arbitrary distribution of membership among the c fuzzy subsets $\mathbf{u}_i$ partitioning $\mathbf{X}$.

Fuzzy c-means objective functionals $J_m : M_{fc} \times \mathbb{R}^{cp} \to \mathbb{R}^+$ are defined as in Eq. (2) where $\mathbf{U} \in M_{fc}$ is a fuzzy c-partition of $\mathbf{X}$; $\mathbf{v} = \{v_1, v_2, \ldots, v_c\} \in \mathbb{R}^{cp}$ with $v_i \in c$ is the cluster center or prototype of $u_i 1 \leqslant i \leqslant c$; $(d_{ik})^2 = \|x_k - v_i\|^2$ and $\|.\|$ is any inner product induced norm on $\mathbb{R}^p$; and weighting exponent $m \in [1, \infty[$.

$$J_m(\mathbf{U}, \mathbf{v}) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^m d_{ik}^2. \tag{2}$$

Examination of J_m reveals that the measure of dissimilarity is $d_{ik} = \|\mathbf{x}_k - \mathbf{v}_i\|$, the distance between each data point $\mathbf{x}_k$ and a fuzzy prototype v_i; the squared distance is then weighted by (u_{ik}^m), the mth power of $\mathbf{x}_k$'s membership in fuzzy cluster u_i. Since each term of J_m is proportional to $(d_{ij})^2$, J_m is a squared error clustering criterion, and solutions of Eq. (3) are the least-squared error stationary points of J_m.

$$\text{minimize}_{M_{fc} \times c} \{J_m(\mathbf{U}, \mathbf{v})\}. \tag{3}$$

An infinite family of fuzzy clustering algorithms, one for each $m \in (1, \infty)$, is obtained via necessary conditions for solutions of Eq. (3).

Assume $\|\cdot\|$ inner product induced, fix m, let $\mathbf{X}$ have at least $c < n$ distinct points, and define $\forall k$ the sets as in Eqs. (4) and (5):

$$I_k = \{i | 1 \leqslant i \leqslant c; d_{ik} = \|\mathbf{x}_k - \mathbf{v}_i\| = 0\}, \tag{4}$$

$$\tilde{I}_k = \{1, 2, \ldots, c\} - I_k, \tag{5}$$

then $(\mathbf{U}, \mathbf{v}) \in M_{fc} \times \mathbb{R}^{cp}$ may be globally minimal for J_m only if Eq. (6) or (7) and the cluster centers are defined as in Eq. (8).

$$I_k = \emptyset \Rightarrow u_{ik} = \frac{1}{\sum_{j=1}^{c} (d_{ik}/d_{jk})^{2/(m-1)}}, \tag{6}$$

$$I_k \neq \emptyset \Rightarrow u_{ik} = 0 \quad \forall i \in \tilde{I}_k, \quad \sum_{i \in I_k} u_{ik} = 1, \tag{7}$$

$$\mathbf{v}_i = \frac{\sum_{k=1}^{n} u_{ik}^m \mathbf{x}_k}{\sum_{k=1}^{n} u_{ik}^m} \ \forall i. \tag{8}$$

The iterative *fuzzy c-means algorithm* [14] determines cluster centers $\mathbf{v}_i$ (Eq. (8)) and the membership matrix $\mathbf{U}$ (Eq. (6)) for the presented input vectors $\mathbf{x}_k$ so that the objective function (Eq. (2)) is minimized. The algorithm steps are as follows:

- step 1: Fix $c, 2 \leqslant c < n$; choose any inner product norm metric for $\mathbb{R}^p$; and fix $m, 1 \leqslant m < \infty$. Initialize $\mathbf{U}^0 \in M_{fc}$. Then at step 1, $l = 0, 1, 2, \ldots$:
- step 2: Calculate the c fuzzy cluster centers $\{v_i^l\}$ with Eq. (8) and $\mathbf{U}_l$.
- step 3: Update $\mathbf{U}_l$ using Eq. (6) and $\{v_i^l\}$.
- step 4: Compare $\mathbf{U}_l$ to $\mathbf{U}_{l+1}$ in a convenient matrix norm: if $\|\mathbf{U}_{l+1} - \mathbf{U}_l\| \leqslant \varepsilon_L$ stop: otherwise, return to step 2.

It is shown in Ref. [14] that the generated sequences $\{(\mathbf{U}^l, \mathbf{v}^l) | l = 0, 1, 2, \dots\}$ at fixed $m > 1$ converge to strict local minima of J_m; or at worst, every convergent subsequence does, provided that the singularity case (7) never occurs. Due to machine roundoff singularity $\mathbf{x}_k = \mathbf{v}_i, \exists i, k$ is usually precluded in practice. Fuzzy c-means has a number of algorithmic parameters: $c, m, \mathbf{U}^0$, $\| \cdot \|_A$, ε_L, for each A there is an infinite family parameterized by m.

Clustering is based on the fuzzy 2-means clustering algorithm, $c = 2$, applied to a collection of n input feature vectors with dimension $p = 65$ distracted from the time–frequency spectrogram obtained as in Section 2.3. The inner norm is chosen to equal the Euclidean distance (Eq. (9)), $m = 2$, $\varepsilon_L = 10^{-5}$ and $\mathbf{U}^0$ is randomly initialized.

$$E_{kl} = \left[\sum_{i=1}^{N} (x_i^{(k)} - x_i^{(l)})^2 \right]^{1/2}. \tag{9}$$

3. Results

3.1. Sound selection

In accordance with Section 2.1 each continuous data-file was pre-processed in order to detect acoustic events. Separate acoustic events of interest are selected out of a fairly constant background noise and saved in separate sound files. This sound begin- and end-detection was performed by applying a triggering algorithm to the absolute value of the signal amplitude of 500 sample points. The triggering threshold was for each experimental data-file determined as a function of the continuous noise-level during recording with a minimum threshold defined by the mean of the absolute values of 500 successively binary noise sample values raised with the standard deviation. So a higher threshold accounted for a higher noise-level which was mainly due to ventilation and in a way the received threshold value could be regarded as a measure for the noisiness of the experimental data-file. An individual sound was captured as successively trigger operations resulted in 'above threshold levels' surrounded by 'below threshold levels'. This implied that each individual 'sound' consists of at least 500 samples corresponding with a minimum duration of 0.02 s.

By pre-processing on all 11 experiments a sound-database of 5890 individual sounds was generated. From those 5319 were clearly classifiable by hearing of which 2034 were recognized as coughing. As described in Section 2.2 the remaining 3285 'no-cough' events comprise both utterances as other environmental sound events. The 571 sounds for which auditive labelling was not possible were not taken into account for further classification since validation was not possible.

3.2. Time–frequency features

Animal calls and their function were mostly studied by interpretation of the commonly used and well-known sound-spectrogram [15]. As an example, Fig. 1 illustrates the spectrogram for the three most occurring experimental pig vocalizations. The time–frequency features for cough,

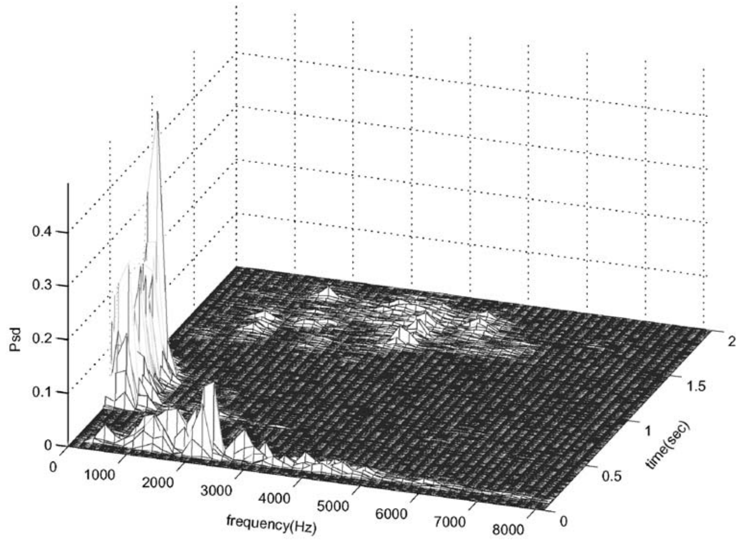

Fig. 1. Spectrogram of pig vocalizations: cough, grunt and scream along increasing time-axis.

grunt and scream plotted along increasing time-axis are obtained as described in Section 2.3. For the obvious reason of non-fixed animal position with respect to the microphone the exact amplitude value is not suitable for sound characterization. The sound intensity or the time-envelope-shape is only taken into account in reference to the criteria for sound selection as explained in Section 3.1. Besides the difference in time duration (e.g. between cough and grunt) the spectrogram reveals a different energy distribution between coughing, grunting and screaming in the time-domain since the greater energy part is situated above and below ± 1000 Hz. It appeared that frequency information was situated well below the Nyquist frequency of 10 kHz.

3.3. Classification of spectral distance

The differences in signal-frequency characteristics, mentioned in Section 3.2, were used to perform a two-class classification of individual sounds, obtained out of a continuous registration by means of the triggering-algorithm described in Section 3.1, into 'cough' or 'other'. A first clustering attempt was made by pattern comparison towards a *reference set* of $q = 20$ coughing sounds. The 20 sound-frequency templates were arbitrarily chosen out of the total database. For each sound the normalized PSD-vector was calculated. This way a *reference PSD-matrix* containing frequency information up to 10 kHz was obtained.

A squared Euclidean distance was used for pattern comparison between the normalized PSD-vector of an individual sound ($\mathbf{PSD}_{test}$), limited to a duration of 5000 sample-points symmetric around the peak-amplitude, towards each reference PSD-vector ($\mathbf{PSD}_{ref}$) included in the reference PSD-matrix. By averaging over the resulting 20 distances each individual sound is represented by d, originating from the normalized PSD-vector, and clustering can be done in one-dimension if a threshold number ε can be found so that the following equation holds for separating cough from no cough:

$$d = \frac{1}{q}\sum_{i=1}^{q} \|(\mathbf{PSD}_{ref})_i - (\mathbf{PSD}_{test})\|^2 < \varepsilon. \tag{10}$$

The threshold ε is determined on the total database of 5319 individual sounds by means of the off-line clustering technique *fuzzy c-means clustering*, briefly summarized in Section 2.4. By considering each sound as belonging to a cluster for some degree, expressed by a membership function MF $(0 \leqslant MF \leqslant 1)$, ε is determined as the spectral-distance value corresponding to $MF = 0.5$, averaged over all experiments. Defuzzification is done based on the received $\varepsilon_{0.5}$ of 1.1394 ($std = 0.1007$) in the one-dimensional distance space and resulted in the requested two-cluster classification. Evaluation of the two-class clustering towards the auditive sound labelling resulted in a 92% correct cough recognition and a 79% correct global classification of the 5319 presented sounds.

Improved overall classification is attempted by applying the fuzzy interpreted spectral distance measure to each channel of an arbitrarily chosen nonuniform ideal filter-bank. The nine frequency ranges used and their respective labelling are presented in Fig. 2. The $\varepsilon_{0.5}$-threshold corresponding to $MF = 0.5$ was determined for each frequency-interval as described in the previous paragraph. Combination of crisp channel-classification output into a computational sum-neuron revealed best classification results when the summed channel-'cough' output exceeded 4. Cough and global correct recognition were slightly improved to 95% and 85%, respectively.

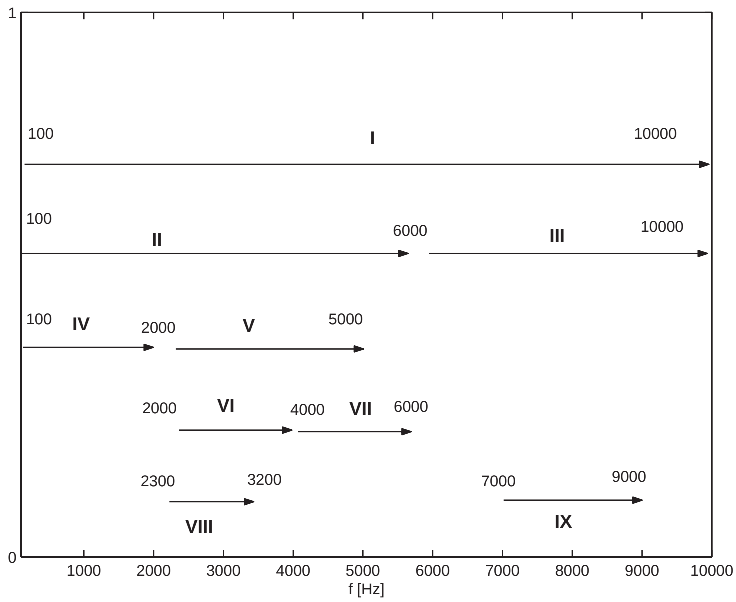

Fig. 2. Frequency ranges and roman labelling.

4. Discussion

To allow automated data analysis, time-domain information is used to define an 'individual sound' out of a continuous recording as explained in Section 3.1. However some precaution both concerning background level and sound shape are necessary. As the method basically involved a triggering on the scaled (500 sample points) signal-amplitude, sounds will almost not be detected in the case of a high or varying background-level. Therefore on-line continuous sound detection would benefit from amplitude-triggering applied to the high-pass frequency-filtered sound-signal, since the constant background noise during recording both for the test installation used as in real piggeries is mostly due to low-frequency fan-noise [16]. Concerning the signal-time envelope, problems may occur if the searched signals show significant dips in amplitude. In this case the triggering algorithm may split up the sound into different parts. As the conditions of dipless time-envelop for the searched cough sounds and of constant background noise during each 30 min experiment is fulfilled, the simple time-triggering approach seems to be sufficient.

Spectral distances were calculated from sound-PSD information up to 10 kHz with ± 170 Hz resolution obtained from 128-windowing (Section 2.3). However no attempt was made to reveal the best frequency resolution for clustering. By considering spectral energy up to 10 kHz all sound energy was taken into account since the highest spectral energy founded (metal sound) was situated below 10 kHz. This is more generally the case for piggeries since according to Ref. [16] no acoustical energy occurs above 10 kHz. The obtained distances, although, are a result of frequency-pattern comparison with a fixed reference of 20 cough sounds. So evolution of cough-frequency information over time is assumed to be limited.

One or more spectral distances were used as input features for off-line two-class fuzzy *c*-means clustering. Obviously the goodness of the proposed classifier design is among others determined by the choice of ε, assuming that such an ε exists. The used values in Section 3.3 were chosen to correspond with an equal membership to both clusters. As the sum of membership degrees is 1, it can be seen as the same membership to both clusters. This is an arbitrary choice and a kind of compromise between correct cough recognition and global correct classification. For instance a higher threshold will result in better cough recognition, but imply a worse global sound classification since more sounds will belong to the cluster interpreted as cough cluster while they are not. Each proposed ε-value of Section 3.3 was the result of averaging over the 11 ε-values defined on the sounds within each experiment.

Next to the choice of ε, the distance function presented in Eq. (10), determines the classification result. The only demand on the used distance metric involved a positive recognition of all reference coughs. However for this distance calculation each frequency component (Euclidian distance) in the global sum, each reference sound has the same impact as all weighting coefficients are 1. So introducing non-1 coefficients in the distance function according to both reference sound and frequency range may improve the resulting classification.

To consider the influence of the varying percentage of 'cough' sounds (from $\pm 10\%$ to $\pm 80\%$) in each of the 11 experimental data-sets cluster-thresholds ε for each of the nine frequency ranges were also determined on the total sound-database originating from all 11 experiments of which 38% was auditively recognized as 'coughing'. Compared to the averaging strategy of Section 3.3 over the 11 obtained thresholds correct 'cough' recognition also reached 95% whereas global correct classification with 83% was 2% less. Since the obtained $\varepsilon_{0.5}$-values for each frequency range were within reach of the standard deviation on the mean $\varepsilon_{0.5}$ averaging seemed a good strategy to cope with the distribution differences from both amount of sounds and 'coughing' between the experimental databases. However since the best clustering result was obtained when the combining sum-neuron for the frequency ranges exceeded 5 instead of 4 it could be remarked that compared to averaging $\varepsilon_{0.5}$-threshold values the union of the 11 databases $\varepsilon_{0.5}$-values are higher, so more sounds were classified as 'cough'.

Till now, distinct frequency-range classification for each of the nine channels was interpreted by a simple sum-neuron. Organizing the channel$_{I,\dots,IX}$-information into fuzzy 'if–then' rules gave an identical classification result since the same spectral distance-input was used, but illustrated some general physical information about the 'cough signal'. For example, introducing a rule by demanding an $\varepsilon_{0.5}$ positive clustering on the spectral distances III and IX included 99% of cough sounds, indicating the absence of spectral energy above ± 6000 Hz for cough sounds.

The proposed pre-processing for sound on- and off-set determination in combination with the classifier-design can be implemented for automated cough recognition from continuous recording inside the test installation on an individual animal. Possible extension to other circumstances will depend on the level and constantness of the background noise and the amount of overlapping vocalizations. An advantage of the proposed classifier design towards other circumstances or small sound variations is the lack for template representation of all possible occurring sounds other than the used cough-reference set. Context dependence on preceding and on following vocalizations, information present in continuous recording, is not taken into account.

5. Conclusion

An on-line pig-cough recognizer system is presented based on time and frequency characteristics of sound registrations on six healthy piglets inside a laboratory installation. Coughing was induced by nebulization of citric acid.

Time information is used for determination of on- and off-set of a possible interesting sound out of a fairly constant assumed background noise level. A two-cluster classification of the obtained individual sounds into 'cough' or 'no cough' was done by applying 2-means fuzzy clustering to the spectral distances of nine arbitrarily chosen frequency ranges and combining the classification outcome in a sum-neuron. Since no special attention was paid to feature extraction, noise reduction, used filter-bank, etc. and clustering was not attempted on a higher dimensional input space, the resulting percentages for correct classification of 95% and 85% for 'coughing' and global sound-database, respectively, are subject for future improvement.

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