31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Segmentation of respiratory signals by Evidence Theory

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***Abstract*— This paper presents an evidential segmentation scheme of respiratory signals for the detection of the wheezing sounds. The segmentation is based on the modeling of the data by evidence theory which is well suited to represent such uncertain and imprecise data. In this paper, we particularly focus on the modelization of the data imprecision using the fuzzy theory. The modelization result is then used to define the mass function. The effectiveness of the method is demonstrated on synthetic and real signals.**

***Index Terms*— Data fusion, segmentation, imprecision, evidence theory, fuzzy membership function.**

I. Introduction

Since the invention of the stethoscope, respiratory sounds acoustic analysis has been used to evaluate and diagnose patients with lung diseases. Nevertheless, this method has a high degree of subjectivity relative to the specialist. During the last decade, sound signal digitization and processing techniques have been developed [1], [2] contributing to make more objective the method by means of quantitative data. Respiratory sounds can be divided into normal and abnormal categories according to their acoustic properties. Wheezes are adventitious sounds with a duration long enough to perceive a musical tone $(100 - 250ms)$. They give information about lung airways activity, showing their obstruction level. This is the reason why those sounds could be of interest to detect respiratory chronic obstructive diseases and study its evolution.

The automatic signal analysis process consists of acquiring signals originating from a source throw one or more sensors. The robustness of the processing techniques can be improved by using more sensors. In such case, information of multiple sensors needs to be combined into one representation. Therefore, data fusion has become in important field of research on medicine engineering. More sophisticated methods of multi-sources data fusion have been proposed [3] such as the Dempster-Shafer (DS) theory of evidence. By allowing the representation of both imprecision and uncertainty, evidence theory appears as a more flexible and general approach compared to the Bayesian theory.

The two notions of uncertainty and imprecision are distinct ones and they must be clearly define. On one hand, the uncertainty represents the belief or the doubt we have on the existence or on the validity of a data. This uncertainty comes from the reliability of the observation made by the system: this observation can be uncertain or erroneous. On the other hand, the imprecision express the fact that we do not have enough knowledge on the datum, thus we describe it with vague terms but its realization is sure. The imprecision results from unavoidable imperfections of the sensors and of the environment map, $i.e.$ the imprecision represents the error associated to the measurement of a value.

Thanks to ANR ASAP for funding, and to Hopitaux Universitaires de Strasbourg (Pr E. Andrès, service de médecine interne, clinique médical B) for the respiratory data available on http://www.websound.fr.

In order to take into account the imprecision and the uncertainty of the respiratory signals, we propose the use of the evidence theory which is well suited to treat such imperfection data. Moreover, this theory provides combination tools to merge data issued from several sources (different respiratory acquisitions) while taking into account their complementarity, their redundancy and their possible opposition (conflict information). Therefore, this theory is convenient to a multi-sources segmentation approach [4].

Our segmentation scheme is based on the use of evidence theory. One of its characteristics is to use the fuzzy theory to modelize and quantify the imprecision degree presented in the data. In particular, we show that this modelization, used in the mass function definition, increases the performance of the segmentation scheme.

This paper is divided as follows. In section II, we present the main aspects of evidence theory. We modelize, in section III, the imprecision degree presented in the signal. In section IV we describe the evidential scheme. In section V, we present segmentation results on a synthetic signal and then on a biological signal.

II. Evidence theory

DS Theory is a mathematical theory of evidence. In a finite discrete space, DS theory can be interpreted as a generalization of probability theory where probabilities are assigned to sets as opposed to mutually exclusive singletons. In traditional probability theory, evidence is associated with only one possible event (or hypothesis) [5]. In DS theory, evidence can be associated with multiple possible events, e.g., sets of events. One of the most important features of DS theory is that the model is designed to cope with varying levels of precision regarding the information and no further assumptions are needed to represent the information. It also allows for the direct representation of uncertainty of system responses where an imprecise input can be characterized by a set or an interval and the resulting output is a set or an interval.

A. The mass function

We suppose the definition of a set of hypotheses Ω called frame of discernment, defined as follows:

$$\Omega = \{H_1, H_2, ..., H_N\}$$

It is composed of N exhaustive and exclusive hypotheses $H_j, j = 1..N$. From the frame of discernment, let 2^Ω be the power set composed with the 2^N propositions A of Ω :

$$2^\Omega = \{\emptyset, \{H_1\}, \{H_2\}, ..., \{H_N\}, \{H_1, H_2\}, ..., \Omega\}$$

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The DS evidence theory provides a representation of both imprecision and uncertainty through the definition of two functions: plausibility (Pls) and belief (Bel), which are both derived from a mass function (m) where m is defined for every element A of 2^Ω, such that the mass value $m(A)$ belongs to the [0, 1] interval:

$$m : \begin{cases} m(\emptyset) = 0 \\ \sum\limits_{A \subset 2^\Omega} m(A) = 1 \end{cases}$$

where $\emptyset$ is the empty set.

The belief and plausibility functions, derived from m, are respectively defined from 2^Ω to [0, 1]:

$$Bel(A) = \sum_{A \subset 2^\Omega, B \subseteq A} m(B) \tag{1}$$

$$Pls(A) = \sum_{A \subset 2^\Omega, B \cap A \neq \emptyset} m(B) \tag{2}$$

In the case of Bayes theory, uncertainty about an event is measured by a single value (probability) and imprecision related to uncertainty measurement is assumed to be null. In the case of DS theory, the belief value of hypothesis A may be interpreted as the minimum uncertainty value about A, and its plausibility value may be interpreted as the maximum uncertainty value of A.

B. Belief attenuation

The mass function m models the piece of evidence brought by a source of information on the different hypotheses of 2^Ω. When this source is considered as imprecise or not completely reliable, the confidence in this source can be attenuated by a factor α and a derived belief structure m_α is then defined by:

$$m_\alpha A = \alpha m(A) \forall A \in 2^\Omega,$$

$$m_\alpha \Omega = 1 - \alpha + \alpha m(\Omega). \tag{3}$$

C. Combination

In the case of segmentation problems dealing with uncertain and imprecise data, it is often interesting to aggregate the information coming from different sources in order to obtain more relevant information. Evidence theory provides reliable tools to combine the knowledge given by different sources. The obtained information is the synthesis of all sources. Thus, the decision process is more confident because it takes into account the whole information of the sources, partially redundant and complementary. The orthogonal rule also called Dempster's rule of combination is the first combination defined within the framework of evidence theory. Let us denote m_1,...,m_L , L masses of belief coming from L distinct sources. The belief function m resulting from the combination of the L sources by means of Dempster's combination rule is defined by:

$$m(A) = m_1 \oplus m_2 \oplus ... \oplus m_L(A) \tag{4}$$

where $\oplus$ is defined by:

$$m_1 \oplus m_2(A) = \frac{1}{1-K} \sum_{B \bigcap C = A} m_1(B).m_2(C) \tag{5}$$

and

$$K = \sum_{B \bigcap C = \emptyset} m_1(B).m_2(C) \tag{6}$$

K is often interpreted as a measure of conflict between the different sources and is introduced as a normalization factor. The larger is K, the more the sources are conflicting and the less sense has their combination. The factor K indicates the amount of evidential conflict. If $K = 0$, this shows complete compatibility, and if $0 < K < 1$, it shows partial compatibility. Finally, the orthogonal sum does not exist when $K = 1$. In this case, the sources are totally contradictory, and it is no longer possible to combine them.

D. Decision

Generally, for most applications, the decision that have to be taken is to choose a simple hypothesis. The authors of [6] propose a decision rule based on a probability function called pignistic probability function defined by:

$$BetP(H_i) = \sum_{H_i \in A} \frac{m(A)}{card(A)} \tag{7}$$

Then, the decision is made according to the MAP estimator.

III. Imprecision quantification

In this section we present some cases where the imprecision is important, and we describe the theory used to modelize and quantify such imprecision.

A. Hypothesis description

Let us denote $P_{i,l}(H_j/Y_i)$, $l = 1..L$, $j = 1..N$, $i = 1...M$, the posterior probability of the class (H_j) given the observation vector Y_i; where M denotes the number of respiratory signal acquisition modes, L the observed signal length and N the number of classes present in the signal. We can distinguish three situations (or three hypothesis) where the imprecision is important:

- $Hyp1$: When the probabilities $\{P_{i,l}(H_j/Y_i)\}$, $j = 1...N$ are too close. Let us take the extreme case where we have two classes and $p_{i,l}(H_1/Y_i) = 0.5$ and $p_{i,l}(H_2/Y_i) = 0.5$. The imprecision in this case is so high that an arbitrary affectation of this sample to unique class H_1 or H_2 has no justification.
- $Hyp2$: In order to regularize the fusion results, we are interested in the zones of transition. Indeed, we assume that the more the transition from a class to the other one, within the same mode, is abrupt, the more the imprecision on the data is important. So, we define a neighborhood $V(l)$ for every sample of the signal in the position l to be able to compare the probabilities $\{P_{i,l}(H_j/Y_i)\}$, $l \in V(l)$.
- $Hyp3$: We assume that more the probabilities $\{P_{i,l}(H_j/Y_i)\}, i = 1..M$ are close more the imprecision in the data is small. In case these probabilities are very different the conflict between the different sources is important. This is based on the assumption that the higher is the conflict, the higher is the imprecision.

B. Hypothesis modelization

These hypothesis are defined to quantify the degree of the imprecision in the data which may be modelized using the fuzzy approach. This is based on the assumption that the concept of the imprecision is an ambiguous concept, $i.e$, all the data are considered as imprecise with a certain degree of membership in this fuzzy set denoted E_{in} : the imprecise data set. Fuzzy set is defined as a collection of ordered pairs of element and its degree of membership (from interval $[0, 1]$) to the set. The degree of membership denotes how much the element belongs to the set. In our case, it means how much the coefficient with specific posterior probability and given those hypothesis is imprecise. For transform of the certain to fuzzy domain, an S membership function f was used. The expression of the proposed f is given by Eq. 8. The range $[a, c]$ is called the fuzzy region. Therefore, to find the degree of imprecision $\mu_{i,l}$ of each coefficient $Y_i(l)$, it is sufficient to define a membership function for every hypothesis, then to choose an operator of fusion. The average operator will be used as a fusion operator.

$$f(x) = \begin{cases} 0 & x \le a \\ \frac{(x-a)^2}{(b-a)(c-a)} & a \le x \le b \\ 1 - \frac{(x-c)^2}{(c-b)(c-a)} & b \le x \le c \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

Where $a \le b \le c$.

- The modelization of $Hyp1$ requires the definition of a membership degree $\mu_{HYP1,i,l}$. To simplify this task, we only consider both classes having the biggest posterior probability $\{P_{i,l}(H_1), P_{i,l}(H_2)\}$. Generally, we measure the distance between two variables means calculating their report. However, to avoid the division by zero and to control the report result, it is better to manipulate the exponential of these two variables. The proposed $\mu_{HYP1,i,l}$ is given by:

$$\mu_{HYP1,i,l} = f_{hyp1}\left(exp\left[P_{i,l}(H_1)\right]/exp\left[P_{i,l}(H_2)\right]\right) \quad (9)$$

  Where f_{hyp1} is the S function used for the $Hyp1$ modelization.
- The modelization of $Hyp2$ requires the definition of a membership degree $\mu_{HYP2,i,l,j,k}$ of E_{in} given the neighborhood $V(l)$. This is means the exponential report of the smallest and the biggest probability of the couple $(P_{i,l}(H_j), P_{i,k}(H_j))$ in order to have a report < 1. The proposed membership function is given then by:

$$\mu_{HYP2,i,l,j,k} = f_{hyp2}\left(\frac{\exp\left[min\left(P_{i,l}(H_j), P_{i,k}(H_j)\right)\right]}{\exp\left[max\left(P_{i,l}(H_j), P_{i,k}(H_j)\right)\right]}\right) \quad (10)$$

  where $k \in V(l)$ and f_{hyp2} is the S function used for the $Hyp2$ modelization.
- The modelization of $Hyp3$ requires the definition of a membership degree $\mu_{HYP3,l,j}$ of E_{in} (we present here the case of two classes). The proposed membership function is given by:

$$\mu_{HYP3,l,j} = f_{hyp3}\left(\frac{exp\left[min\left(P_{1,l}(H_j), P_{2,l}(H_j)\right)\right]}{exp\left[max\left(P_{1,l}(H_j), P_{2,l}(H_j)\right)\right]}\right) \quad (11)$$

  where f_{hyp3} is the S function used for the $Hyp3$ modelization.

Finally, the expression of $\mu_{i,l}$ is given by:

$$\mu_{i,l} = \frac{\mu_{HYP1,i,l} + \sum\limits_{k=1..K, j=1..N} \mu_{HYP2,i,l,j,k} + \sum\limits_{j=1..N} \mu_{HYP3,j,l}}{1 + K.N + N} \quad (12)$$

Where $K = card(V(l))$.

IV. Fusion scheme

Now, we consider the mass function modelization problem. We will use the probabilities $P_{i,l}(H_j/Y_i)$ and the membership function $\mu_{i,l}$ to define the mass function $m(i, l)$ for each sample $Y(i, l)$ by respecting a certain number of properties such as the coherence with the bayesian model in case of imprecision absence. We can distinguish two extreme situations. The first is characterized by the total imprecision absence ($\mu_{i,l} = 0$), in this case only the mass functions of the simple classes are non-zero. The second situation is characterized by the total ignorance ($\mu_{i,l} = 1$): all the mass functions of the simple class are null. The expression of the proposed non-normalized mass function $m(i, l)$ is given by:

1-If N=2;

$$m_{\{i,l\}}(\{H_1\}) = (1 - \mu_{i,l}).P_{i,l}(H_1/Y_i)$$

$$m_{\{i,l\}}(\{H_2\}) = (1 - \mu_{i,l}).P_{i,l}(H_2/Y_i)$$

$$m_{\{i,l\}}(\{H_1, H_2\}) = \mu_{i,l}.max(p_{i,l}(H_1/Y_i), P_{i,l}(H_2/Y_i)) \quad (13)$$

2- If $N > 2$

$$m_{\{i,l\}}(\{H_j\}) = (1 - \mu_{i,l}).P_{i,l}(H_j/Y_i) \qquad j = 1..N$$

$$m_{\{i,l\}}(\{H_j, H_k\}) = \mu_{i,l}.max(P_{i,l}(H_1/Y_i), P_{i,l}(H_2/Y_i)) \quad j, k = 1..N \; and \; j \ne k$$

$$m_{\{i,l\}}(\{\Omega\}) = \mu_i(l).max(P_{i,l}(H_1)/Y_i, ..., P_{i,l}(H_N/Y_i)) \quad (14)$$

The fusion algorithm is as follows:

Algorithm 1 fusion scheme

Calculate the membership function $\mu_{i,l}$ (12)
Calculate the mass function $m(i, l)$ (14)
Calculate the combined mass function m (4)
Decision rule (7)

V. Fusion results and discussion

This part describes some segmentation results obtained with the proposed segmentation scheme. This method was applied both on synthetic signal designed to fit the characteristics of the wavelet packets respiratory signal assumed to follow a zeros mean generalized Gaussian GG distribution [7] and real signal given by Pr E.Andrès (Hopitaux Universitaire de Strasbourg).

A. Fusion results on synthetic data

The main advantage of using simulated data is that we perfectly know the characteristics of the data such as the class membership of each coefficient. For this, we generate a multi-modes GG sequence ($M = 2$, $L = 600$, $N = 4$) shown in Fig. 1. The different values of hyperparameters of the multi-modes GG are presented in Tab. I . The posterior probabilities $P_{i,l}(H_j/Y_i)$ were calculated using the method presented in [7].

	class 1		class 2		class 3		class 4	
	α	σ^2	α	σ^2	α	σ^2	α	σ^2
mode 1	1	0.15	2	0.35	5	0.75	10	1
mode 2	1	0.1	2	0.4	5	0.8	10	1.2

TABLE I

Values of shape parameters α and variances σ^2 of the four classes in each mode.

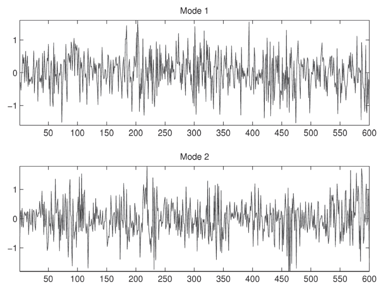

Fig. 1. The synthetic signal used for the simulation.

In order to emphasize the benefit of the proposed approach and particulary the use of fuzzy theory to quantify the imprecision degree presented in the data, two different segmentation methods were applied to the synthetic signal presented in Fig. 1 : a respiratory sounds segmentation method using probabilistic fusion which is based on HMC (Hidden Markov Chain) [7] (a probabilistic scheme) denoted (M1) and our segmentation method (a DS scheme) denoted (M2). The Tab. II presents the segmentation error rate for different values of SNR. We can easily observed the advantage of using an evidential fusion scheme comparing to a probabilistic fusion scheme. The segmentation error rates results are confirmed by the visual results presented in Fig. 2.

SNR	9dB	4dB	0dB	-4dB
M1	4.55%	7.35%	11.57%	15.66%
M2	2.66%	4.71%	7.88%	11.36%

TABLE II
ERROR RATES ON THE SYNTHETIC DATA.

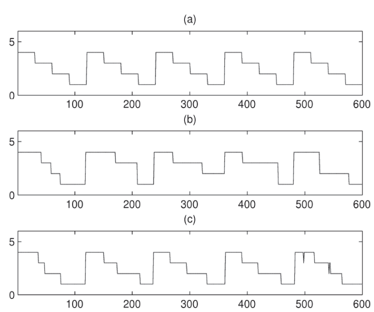

Fig. 2. (a) ground truth, (b) segmentation result using M1, (c) segmentation result using M2.

B. Fusion results on real data

Now, we consider the problem of the real signal segmentation. In our case, it corresponds to the asthma sound. Firstly, we calculate the wavelet packet transformation of the signal to have a higher flexibility in terms of scalability in resolution and distortion. Then, we apply our segmentation method and the M1 method to the asthma wavelet packet coefficients. We obtain the segmentation results presented in Fig. 3. The Wheeze wavelet packet coefficients are presented in Fig. 3(a) and (b) with dotted lines. As one can see, only our method detected the presence of the wheeze. This detection allows us to study the characteristics of the wheezing sound such as its duration. Indeed, the parameter that best correlates with other clinical indices of asthma severity is wheeze duration [8].

The segmentation result shows that the proposed evidential fusion scheme using both the imprecision and the uncertainty on the data increases the effectiveness of the segmentation while segmentation result of M1 are effected, in part, by the regularizing aspect of the HMC model, which tends to drown some significant details of the signal.

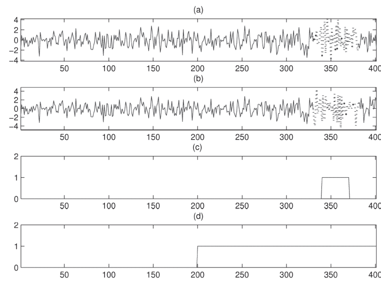

Fig. 3. (a) asthma coefficients mode 1, (b) asthma coefficients mode 2, (c) segmentation result using our segmentation scheme, (d) segmentation result using M1.

VI. CONCLUSION

In this paper, we proposed a new evidential segmentation scheme in order to detect the presence of wheeze in the respiratory signal. This method combined the modeling of the knowledge by means of the evidence theory and integrates the fuzzy theory to quantify the imprecision degree presented in the signal. This approach is theorically validated in this paper, and we currently work on future development on a raw biological signal data base in collaboration with physicians from Hopitaux Universitaires de Strasbourg.

REFERENCES

[1] RB Urquhart, J. McGhee, JE Macleod, SW Banham, and F. Moran, "The diagnostic value of pulmonary sounds: a preliminary study by computer-aided analysis.," *Comput Biol Med*, vol. 11, no. 3, pp. 129–39, 1981.

[2] ARA Sovijärvi, J. Vanderschoot, and JE Earis, *Computerized Respiratory Sound Analysis (CORSA): Recommended Standards for Terms and Techniques: ERS Task Force Report*, Munksgaard, 2000.

[3] E. Waltz and J. Llinas, *Multisensor data fusion*, Artech House Boston, 1990.

[4] J. Gordon and E.H. Shortliffe, "The Dempster-Shafer theory of evidence," *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project*, pp. 272–292, 1984.

[5] G. Shafer, "A mathematical theory of evidence," 1976.

[6] P. Smets, "Constructing the pignistic probability function in a context of uncertainty," in *Uncertainty in Artificial Intelligence*, 1990, vol. 5, pp. 29–39.

[7] S. Lecam , A. Belghith , F. Salzenstein , C. Collet , "Wheezing sounds detection using multivariate generalized gaussian distributions," in *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP'09*. April 18-25th, 2009, Taipei, Taiwan, april 2009.

[8] RP Baughman and RG Loudon, "Lung sound analysis for continuous evaluation of airflow obstruction in asthma," *Chest*, vol. 88, no. 3, pp. 364–368, 1985.