AUTOMATIC SEGMENTATION AND CLASSIFICATION OF BOWEL SOUNDS

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Abstract: **The general framework of this communication is phonoenterography. The goal is the development of a clinical diagnostic tool based on multichannel abdominal sound monitoring. Unsupervised and supervised data processing should aid the diagnostics. We address here the segmentation, feature extraction and classification of detected events.**
Keywords: **bowel sounds, segmentation, feature extraction, classification, wavelet transform**

Introduction

Bowel sounds (BS) have been attracting attention for a long time, since they possibly carry functional information about the digestive tract. Studies dedicated to the physiological interpretation of BS suggest their relationship to normal and / or pathological digestive phenomena. Following characteristics of individual sounds and complete signals have to be scrutinized: frequential sound content, sound intensity and duration, silence duration, sound localization [1-4].

Nevertheless, two problems have to be settled:
- recorded data have to be pre-processed to permit direct access to BS. We have addressed the first steps of the pre-processing (wavelet denoising and segmentation) in a previous work [5] (see also references therein);
- extracted BS have to be interpreted accurately. All cited features are embedded in the wavelet representation, sound localization excepted. Localization is allowed by the use of several microphones.

In this paper, we present the last stages of preprocessing, followed by several steps of feature extraction and classification, adapted to bowel sounds.

Materials and Methods

In order to facilitate an auditive medical validation, we have attached three electret pressure microphones to mechanical stethoscope heads, placed on the abdominal area as follows: the first one on the pylorus area (10 cm above the umbilicus), the second one on the descending colon area (lower left quadrant) and the third one on the ileo-caecal area (lower right quadrant). After band-pass [50-2250 Hz] anti-aliasing filtering, the signals were digitised by a 12 bit Analog-Digital Converter, at a sampling rate of 5 kHz. Signals were recorded on healthy subjects, for 10 to 15 minutes, before and after lunch.

In medical terms, a BS is an audible event that potentially carries information about a physiological phenomenon. In signal processing terms, a BS becomes then a part of the signal that can be extracted from noise and has certain informative characteristics (power, frequency content, duration …). To extract the events from the recorded signal (denoising and first segmentation), we use the wavelet transform, as shown in [5, 6]. Moreover, the wavelet representation of a BS allows the extraction of the informative features cited above.

After denoising and first segmentation [5], we have implemented three new pre-processing steps:
- low-power event elimination: the non-audible BS (with power less than the mean power of noise, computed as the mean power of "silent" parts of the signal).
- concatenation: the events separated by less than 100 ms are considered as generated by the same phenomenon. This concatenation is implemented as a morphological closing of the binary segmentation signal.
- three-channel elimination: an event is deleted if it starts later, stops earlier and has a power less than an event appearing on another channel.

These three steps can be seen as a way to improve the signal processing definition of the event, in order to get it closer to the medical definition, and as a first stage of multi-channel localisation of the sounds. As a result, the number of BS considerably decreases (from ≈172 to ≈25 ev./min.), so the classification is facilitated.

The next stage, before classification, is the feature extraction. Despite some attempts, e.g. [1,4], the characterisation and the classification of bowel sounds are not well defined. Moreover, the design of a feature extractor is intimately connected to the design of the classifier [7], since the latter validates the significance of the chosen features. Therefore, we have treated the two problems together.

We have chosen a completely unsupervised clustering method: we don't impose neither the number of clusters nor the position of their centroids. Instead, we use a hierarchical clustering technique, and we test several metrics and linkage methods. This unsupervised clustering is followed by an optimisation procedure that takes into account local characteristics of the data and outlier detection (using Mahalanobis metric). The method is applied to a large data-base containing bowel sounds recorded on a healthy subject, on the three channels and in different physiological conditions (before and after lunch). The result is used as training set for the next step: the supervised classification of recorded signals by linear discriminant analysis (LDA).

Results

We perform the unsupervised classification using different feature sets. The first one and the most exhaustive is the complete wavelet coefficient set for each event. But, as the duration of a bowel sound can be rather important (up to 5 seconds), the dimension of the wavelet decomposition and, as a result, of the feature space, becomes prohibitive ($\approx 10^5$).

A second tested feature set was created by calculating the power distributed on each frequency scale of the wavelet decomposition (the depth we have chosen equals 8 [5]) and the power distributed on equal time intervals, having the duration determined by the lowest frequency wavelet. As the feature space dimension remains important (between 80 and 120 axis), we perform an intermediate step of Principal Component Analysis. The main disadvantage of this approach is the loss of the physical significance of the features.

Finally, the third feature set was obtained by using physically significant characteristics: the power of the event, the main frequency and the duration. The power was normalised by the mean noise power, in order to take into account the variation of the stethoscope pressure between recordings. The main frequency was obtained as the maximum value of the reconstructed frequency spectre using wavelets Fourier transforms.

In the feature spaces presented above, we have tested different hierarchical clustering algorithms, using different metrics (Euclidian, Mahalanobis, City-Block) and linkage methods (Single, Complete, Centroid, Average, Ward). To evaluate the solutions, we used the cophenetic coefficient, the resulted number of clusters (as we know that medical empirical classification yields 3-5 types of sounds) and the computational complexity.

Finally, after comparative tests, the chosen solution was the clustering in the physical characteristics space (3D) using an Euclidian metric and the centroid linkage method. The optimisation procedure of the resulted classification consists in three steps:

- outliers detection: outliers, defined as points having a probability less than 0.01, are detected using a chi-square test on the Mahalanobis distances distribution.
- cluster merging: a cluster is merged into another if more than a third of its points (which are not outliers) belongs also to the second one (that is, are not outliers).
- re-assignation: frontier points and / or outliers are re-assigned to another cluster if they respect the previous conditions (they are not outliers).

This algorithm is used to create a training set for the LDA, which is applied to classify other recordings, taken in different physiological conditions. The histograms of the classes are presented in Figure 1.

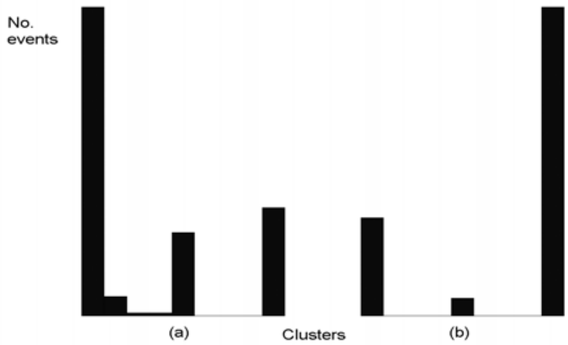

Figure 1: Cluster distribution for 2 recordings, taken under similar conditions, for the same subject: (a) healthy; (b) gastro-enteritis. The training set was determined from other healthy subjects. The last cluster at the right represents the outliers.

Discussion

The implemented methods were adapted to the specificity of our problem (number and shape of clusters unknown), and the results are promising. Different recordings taken under the same conditions show a similar distribution of the events, while a transfer between clusters can be observed for abnormal conditions (gastro-enteritis) (see Figure 1). Still, the presented algorithms can be improved in many aspects: the optimisation of the unsupervised stage can be modified to take into account not only the shape of the clusters (Mahalanobis metric), but also their volume and probability distribution [8]. Other methods of supervised classification can be tested also.

Conclusions

The developed method shows that automatic clustering can be performed on BS. The classification was validated by medical expertise. Even if, as seen in the discussion, it can be substantially improved, the results are satisfying and clinical testing on pathological signals (before and after surgical intervention) is considered.

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