

# Principal component analysis and interpretation of bowel sounds

R. Ranta<sup>1</sup>, V. Louis-Dorr<sup>1</sup>, C. Heinrich<sup>2</sup>, D. Wolf<sup>1</sup>, F. Guillemin<sup>1</sup>

<sup>1</sup>CRAN, UMR INPL-CNRS 7039, Nancy, France

<sup>2</sup>LSIIT, UMR ULP-CNRS 7005, Strasbourg, France

**Abstract**— This paper presents a method for abdominal sounds analysis based on principal component analysis (PCA). The first steps (wavelet denoising and segmentation, followed by spatial localization) were presented in previous works. After extracting physical features (activity indices) from long time six channel recordings, we propose a reduced representation space obtained by PCA and we present our results in phonoenterogram analysis.

**Keywords**—bowel sounds, principal component analysis

## I. INTRODUCTION

Physiological sounds auscultation is a classical and widely employed medical investigation method. It is well developed for cardiac and pulmonary sounds, but much less applied in the field of phonoenterography. Nevertheless, gastrointestinal sounds have been studied as early as 1905 [1], and they have been focusing more and more attention during the last decade [2–6].

It seems obvious that there is some information on the digestive process contained in bowel sounds recordings (phonoenterograms), but its extraction and interpretation remains difficult because of the specificity of the abdominal sound signals: the sounds may appear at irregular time intervals, they appear at different abdominal locations, they are patient dependent, and they need to be analysed over long periods of time. Still, several authors mention pre-processing [2, 7, 8], localization [5, 9] and analysis [3, 4, 6, 10] methods. Their results prove that one can eventually distinguish between different phases of the digestive cycle, different pathologies and different abdominal locations, using activity indices as number of sounds per minute, total duration of sounds, etc.

In this paper, we propose a method that aims to use and complement the different analysis methods presented in the literature. The goal is to shed new light upon dependencies between most popular activity indices in order to facilitate the interpretation and analysis of phonoenterograms. This allows the creation of an optimal representation space, necessary for devising an objective bowel sounds diagnostic and analysis tool, which is the ultimate goal of this research project. We present here results obtained on healthy subjects.

## II. PHONOENTEROGRAM RECORDING AND PRE-PROCESSING

Phonoenterograms were recorded according to a pre-defined protocol: the six-channels recordings were performed during 168 minutes, at a sampling frequency of 5 kHz,

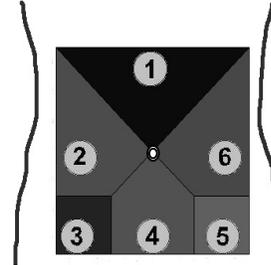


Fig. 1. Stethoscope placement and abdominal regions

immediately following a standardized breakfast. The six stethoscopes were placed as in Figure 1.

In order to analyse abdominal sound signals, one needs to pre-process them: they must be denoised and segmented in individual sounds, which must be further localized in the case of multi-channel recordings. We will not present here in details these pre-processing steps (the reader is referred to [2, 7–10]). Our denoising algorithm [7, 8], which develops the method presented in [2], is based on orthogonal wavelets and allows us to extract individual gastrointestinal sounds from phonoenterograms. The localization technique is performed according to [9] and associates each individual sound to a single channel and to its corresponding abdominal region (see Figure 1). For each sound, we have computed the most popular physical features: the duration, the energy and the main frequency, as in [3–6, 9, 10].

## III. FEATURE EXTRACTION

Several activity indices, based on the physical features mentioned above, are proposed in the literature (see for example [3–6]). We have identified nine of them, evaluated for each channel and for minute of recording: the number of sounds ( $N_m$ ), the total energy ( $E_m$ ), the total duration of sounds in percents ( $D_m$ ), the mean energy of sounds ( $E_\mu$ ), their mean duration ( $D_\mu$ ), their mean power ( $P_\mu$ ), their mean main frequency ( $f_\mu$ ), their mean acoustic intensity ( $I_\mu$ ) and the mean duration of silence periods between sounds ( $D_{s,\mu}$ ).

Each minute of recording can then be represented as a point in the nine-dimensional space obtained from the nine activity indices. Still, interpreting this information reveals to be difficult because of the high dimension of the representation space and, furthermore, because of the probable redundancy of the nine features. Our goal is to analyse the dependencies between the above mentioned activity indices, to eliminate redundancy and to reduce the dimension of the representation space. The classical method is the principal component analysis (PCA).

#### IV. PRINCIPAL COMPONENT ANALYSIS

##### A. Method and results

The first step before applying PCA techniques to a set of data is the definition of this set: we have recorded 504 minutes (three healthy subjects) of abdominal sounds using a six channel recorder. Each of the 3024 minutes is described by the nine activity indices (features) mentioned above. This information is stored in a 3024 x 9 matrix of data  $\mathbf{D}$ . In order to check the redundancy of the nine features, we have computed the correlation matrix  $\mathbf{R}$  (Table 1). As expected, there are significant redundancies between features ( $N_m$  and  $D_m$  for example).

TABLE I  
FEATURE CORRELATION MATRIX  $\mathbf{R}$

	$N_m$	$E_m$	$D_m$	$E_\mu$	$D_\mu$	$P_\mu$	$f_\mu$	$I_\mu$	$D_{s,\mu}$
$N_m$	1.00	0.20	0.81	0.05	0.09	0.15	0.17	0.17	-0.48
$E_m$	0.20	1.00	0.40	0.72	0.24	0.64	0.07	0.29	-0.08
$D_m$	0.81	0.40	1.00	0.30	0.49	0.29	0.06	0.37	-0.41
$E_\mu$	0.05	0.72	0.30	1.00	0.52	0.61	0.04	0.38	-0.04
$D_\mu$	0.09	0.24	0.49	0.52	1.00	0.26	0.05	0.50	-0.03
$P_\mu$	0.15	0.64	0.29	0.61	0.26	1.00	0.19	0.72	-0.10
$f_\mu$	0.17	0.07	0.06	0.04	0.05	0.19	1.00	0.31	0.11
$I_\mu$	0.17	0.29	0.37	0.38	0.50	0.72	0.31	1.00	-0.13
$D_{s,\mu}$	-0.48	-0.08	-0.41	-0.04	-0.03	-0.10	0.11	-0.13	1.00

PCA transforms original data matrix  $\mathbf{D}$  (after normalization) in a new matrix  $\mathbf{M}$  having the same dimension but with orthogonal (non-redundant) columns. Each phonoenterogram minute is described by nine new decorrelated features  $c_1$  to  $c_9$  (principal components). Moreover, the principal components are ordered by their variance (Table 2). This ordering allows to choose a reduced number of features describing the data (phonoenterogram minutes) and still preserving the most important part of the dispersion (variance).

TABLE II  
PRINCIPAL COMPONENTS VARIANCE (ABSOLUTE VALUE, PERCENTAGE AND CUMULATED PERCENTAGE)

	var.	%	cum. %
$c_1$	3.51	39.0	39.0
$c_2$	1.76	19.6	58.6
$c_3$	1.16	12.9	71.5
$c_4$	0.94	10.4	81.9
$c_5$	0.76	8.5	90.3
$c_6$	0.50	5.4	95.7
$c_7$	0.20	2.3	98.0
$c_8$	0.11	1.3	99.3
$c_9$	0.06	0.7	100.0

Using the Kaiser criterion [11], one can choose the principal components having a variance larger than 1 (in this case the first three). The generated space is 3-dimensional

and preserves more than 70% of data dispersion. Still, in order to analyse the results, one must associate a physical interpretation to these new features. This is done by computing the correlations between the ancient features (activity indices) and the new ones (principal components).

An intuitive way of representing these correlations involves correlation circles [11]. As seen in Figure 2, each activity index is plotted as a point onto the planes generated by the first three principal components  $c_1$ - $c_3$ . The coordinates of each point are given by the correlation between the corresponding activity index and the principal components (the orthogonal axis).

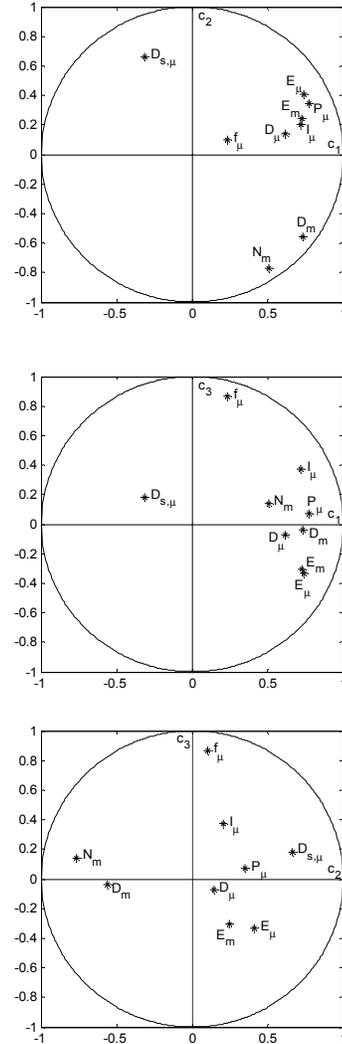


Fig. 2. Correlation circles

The first principal component  $c_1$  can be seen as a size variable. It is mainly correlated with energetic measures as  $E_m$ ,  $E_\mu$ ,  $P_\mu$ , or  $I_\mu$ , so we propose to interpret it as an activity level, or *sound level* measure. The second principal component  $c_2$  is rather anti-correlated with time measures as  $D_m$  or  $N_m$ , and quite correlated with  $D_{s,\mu}$ , which suggest an interpretation as a measure of sound absence or *sparsity*.

Components  $c_1$  and  $c_2$  are not antinomic since it is possible to have a high sound level scattered on relatively few sounds. Finally, the third principal component  $c_3$  is related to the mean frequency  $f_\mu$  and can be interpreted as a *pitch* measure of the minute.

### B. Data analysis

The most common way of analysing data in the PCA framework is to search for possible differences between pre-defined subgroups. We therefore considered separate subgroups, each one consisting in the minutes recorded on a particular channel, which in fact means that we analyse possible differences between abdominal regions. In order to visualize these differences, the barycenter of each subgroup (the average or standard minute of each region) is projected onto the principal planes generated by the first three principal components  $c_1$ - $c_3$  (Figure 3).

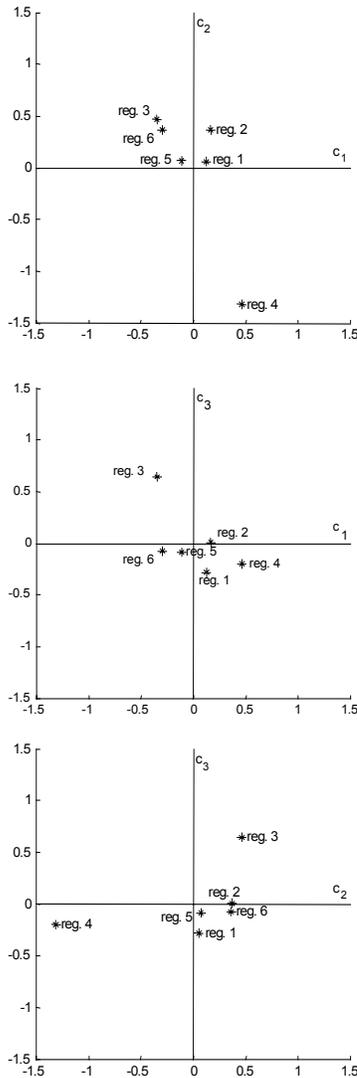


Fig. 3. Projections of the 6 abdominal regions onto the principal planes  $c_1$ - $c_2$ ,  $c_1$ - $c_3$ ,  $c_2$ - $c_3$ .

Based on Figure 3, one can observe that region 4 (corresponding to the mid-lower part of the abdomen) is strongly characterized by negative values of the  $c_2$  principal component, that is, this region is very rich in sounds, compared to the other regions. Using the same reasoning, the third region (lower-right abdomen) seems to be characterized by higher frequency sounds than those recorded in the other regions.

We have equally verified that the previous observations apply to each of the three subjects we have recorded. Certainly, more recordings are needed in order to state that normal phonoenterograms exhibit these characteristics.

Another important aspect and a possible way of verifying these observations consists in studying the time-evolution of principal components  $c_2$  and  $c_3$  for the two regions (reg. 4 and reg. 3). The question is: are the observations we made about sparsity ( $c_2$ ) and pitch ( $c_3$ ) valid all the time, or do they change during the digestive cycle?

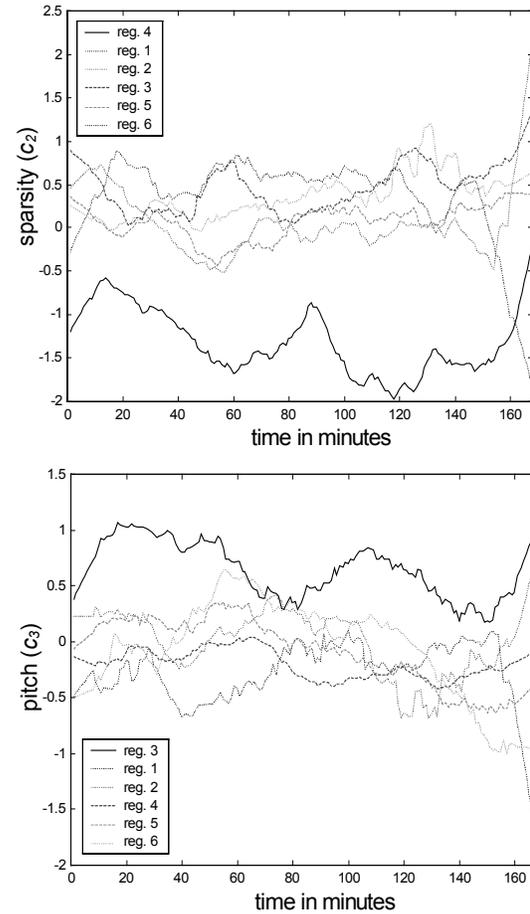


Fig. 4. Time evolution of principal components  $c_3$  and  $c_2$  for the six abdominal regions (smoothed values).

As seen in Figure 4, time evolution of the pitch and of the sound sparsity of each minute confirms that the third abdominal region produces higher frequency sounds and the fourth region is richer than the others.

## V. CONCLUSION AND FUTURE RESEARCH

Our primary goal in this paper was to propose an objective method adapted to abdominal sounds analysis. This method, based on principal component analysis, takes into account various ways for describing gastrointestinal activity according to a set of activity indices presented in the literature. Given the large number of activity indices and their redundancy, we have proposed a PCA method in order to diminish the dimension of the representation space and to eliminate redundancy.

We have also given physical interpretation to the first three principal components by studying their correlation with the original activity indices. The new 3-dimensional representation space generated by these components is used to analyse data: we characterize different abdominal regions by their sound activity. It seems, after examining the 3024 minutes of phonoenterogram that we recorded following a standardized protocol, that we can objectively affirm that the mid-lower abdomen is richer in sounds than the other regions, and that the sounds generated in the lower left abdomen are of higher frequency.

Still, our recordings have been taken on only three patients, and even if our analysis is performed on a great quantity of data (3024 minutes), it needs to be confirmed by introducing more healthy subjects in the protocol.

Another important underway development aims to analyse pathological phonoenterograms and to study their possible differences with the recordings obtained on healthy subjects, using the method developed in this paper.

Finally, the new representation space created by PCA can be used for classification purposes, as clustering algorithms perform better in low dimensional spaces. This can be seen as a step towards the objective classification of abdominal sound activity and its application to medical diagnostics and research, which is the final goal of our project.

## REFERENCES

- [1] W. Cannon, "Auscultation of the rhythmic sounds produced by the stomach and intestines," *Am. J. Physiology*, vol. 14, pp. 339–353, 1905.
- [2] L. Hadjileontiadis *et al.*, "Enhancement of bowel sounds by wavelet-based filtering," *IEEE Trans. Biomedical Engineering*, vol. 47, no. 7, pp. 876–886, 2000.
- [3] T. Tomomasa *et al.*, "Gastrointestinal sounds and migrating motor complex in fasted humans," *Am. J. Roentgenology*, vol. 94, no. 2, pp. 374–381, 1999.
- [4] B. Craine, M. Silpa, and C. O'Toole, "Enterotachogram analysis to distinguish irritable bowel syndrome from Crohn's disease," *Digestive Diseases and Sciences*, vol. 46, no. 9, pp. 1974–1979, 2001.
- [5] B. Craine, M. Silpa, and C. O'Toole, "Two-dimensional positional mapping of gastrointestinal sounds in control and functional bowel syndrome patients," *Digestive Diseases and Sciences*, vol. 47, no. 6, pp. 1290–1296, 2002.
- [6] H. Yoshino, Y. Abe, T. Yoshino, and K. Ohsato, "Clinical application of spectral analysis of bowel sounds in intestinal obstruction," *Dis. Col. Rectum*, vol. 33, no. 9, pp. 753–757, 1990.

- [7] R. Ranta, Ch. Heinrich, V. Louis-Dorr, and D. Wolf, "Interpretation and improvement of an iterative wavelet-based denoising method," *IEEE Signal Processing Letters*, vol. 10, no. 8, pp. 239–241, 2003.
- [8] R. Ranta, V. Louis-Dorr, Ch. Heinrich, D. Wolf, and F. Guillemin, "Débruitage par ondelettes et segmentation de signaux non-stationnaires: réinterprétation d'un algorithme itératif et application à la phonoentérographie," (in French) *Traitement du Signal*, vol. 20, no. 2, pp. 119–135, 2003.
- [9] R. Ranta, V. Louis-Dorr, Ch. Heinrich, D. Wolf, and F. Guillemin, "Towards an acoustic map of abdominal activity," *Proc. of the 25<sup>th</sup> IEEE-EMBS Conference, EMBC'03*, Cancun, Mexico, pp: 2769–2772, 2003.
- [10] R. Ranta, "Traitement et analyse de signaux sonores physiologiques: application à la phonoentérographie," (in French), PhD Thesis, INPL Nancy, France, 2003.
- [11] G. Saporta, *Probabilités, analyse des données et statistique* Technip, France, 1990.