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Recurrence Quantification Analysis for the Classification of Lung Sounds

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Abstract. The Recurrence quantification Analysis technique is used for analyzing and classifying lung sounds recorded from different typologies of pulmonary diseases. The results show good performances in identifying the pathologies and provide interesting clinical and diagnostic features.

INTRODUCTION

Pulmonary disease is a major cause of ill-health throughout the world [4]. In Europe, chronic obstructive pulmonary disease (COPD) and asthma have been estimated to affect between 10 and 25% of the adult population. Pulmonary infections such as acute bronchitis and pneumonia are common, and interstitial lung disease is increasing in incidence. The diagnosis of these common chest diseases is facilitated by pulmonary auscultation using a stethoscope. Auscultation with a stethoscope has many limitations. It is a subjective process that depends on the individual’s own hearing, experience and ability to differentiate between different sound patterns. It is not easy to produce quantitative measurements or make a permanent record of an examination in documentary form. Long-term monitoring or correlation of respiratory sound with other physiological signals is also difficult. Moreover, the stethoscope has a frequency response that attenuates frequency components of the lung sound signal above about 120 Hz, and the human ear is not very sensitive to the lower frequency band that remains.

Digital recording is a reliable and quantitative method for an objective assessment of lung sounds for diagnosis of pulmonary diseases [5]. The study of lung sounds provided the evaluation of important features, such as correlation with other physiological signals, comparison of the sound at different times during the progression of respiratory disease, detection of characteristics that are not detectable by human ear.

Nevertheless, the analysis of lung sounds has not yet found a major place in diagnosis of respiratory diseases. Lung sounds are non-stationary in healthy normal subject and strongly non-stationary in abnormal subject. Moreover, as many biological and physiological signals, they exhibit an apparently random behavior which is often punctuated with seemingly deterministic process. The frequency analysis does not allow one for detecting significant properties of the signal, while techniques based on the shape of the signal are often limited by noise.

In this paper a completely new approach based on the Recurrence Quantification Analysis is proposed. The method is based on the assumption that the signal is not random but shows several recurrence features, such as periodic or chaotic behavior. In particular, it assumes that, by using the information provided by the signal, it is possible to investigate some features of the underlying dynamical system that has produced the signal and analyze the recurrence properties of its trajectory in the reconstructed phase space.

TIME SERIES ANALYSIS BASED ON RECURRENCES

Starting from a time series \( s_1, \ldots, s_N \), where \( s_i = s(i\Delta t) \) and \( \Delta t \) is the sampling time, the system dynamics can be reconstructed using the theorem of Takens and Mañé [6]. The reconstructed trajectory \( X \) is expressed as a matrix in which each row is a phase space vector:

\[
X = \begin{bmatrix} x_1, x_2, \ldots, x_M \end{bmatrix}^T,
\]
where \( \mathbf{x}_i = [s_i, s_{i-\tau}, \ldots, s_{i-(D_E-1)\tau}] \) and \( M = N - (D_E - 1)\tau \). The matrix is characterized by two key parameters: the Embedding Dimension \( D_E \) and the Delay Time \( \tau \).

After reconstructing the dynamical system, the presence of recurrences in the trajectory is investigated, in fact recurrent behaviors are typical of biological and physiological systems. In the framework of dynamical systems, this implies the recurrence of state vectors, i.e., states with large temporal distances may be close in state space.

The Recurrence Plot is a two dimensional binary diagram representing the recurrences that occur in an \( m \)-dimensional phase space within an arbitrarily defined threshold \( \varepsilon \) at different times \( i, j \). The RP is easily expressed as a two dimensional square matrix with ones and zeros representing the occurrence (ones) or not (zeros) of states \( \mathbf{x}_i \) and \( \mathbf{x}_j \) of the system:

\[
R_{ij} = \Theta(\varepsilon - ||\mathbf{x}_i - \mathbf{x}_j||), \quad \mathbf{x}_i \in \mathbb{R}^m, \quad i, j = 1, \ldots, N, 
\]

where \( N \) is the number of measured states \( \mathbf{x}_i \), \( \Theta(\cdot) \) is the step function, and \( || \cdot || \) is a norm. In the graphical representation, each non-zero entry of \( R_{ij} \) is marked by a black dot in the position \((i, j)\). Since any state is recurrent with itself, the RP matrix fulfills \( R_{ii} = 1 \) and hence it contains the diagonal Line of Identity (LOI). To compute an RP, a norm must be defined. Usually the \( l_{\infty} \) norm is used, because it is independent of the phase space dimension and no rescaling of \( \varepsilon \) is required. Furthermore, special attention must be paid to the choice of the threshold \( \varepsilon \). Although there is not a general rule for the estimation of \( \varepsilon \), the noise level of the time series plays an important role in its choice. Usually, \( \varepsilon \) is chosen as a percentage of the diameter of the reconstructed trajectory in the phase space, not greater than 10% [2].

An RP is characterized by typical patterns, whose structure is helpful for understanding the underlying dynamics of the time series. For example, a homogeneous distribution of points is usually associated with stationary stochastic processes, e.g. gaussian or uniform white noise, while periodic structures indicate periodic behaviors; drifts in the structure of the recurrences are often due to a slow variation of some parameter of the underlying system; white areas or bands indicate non stationarity and abrupt changes in the dynamics.

Because of the screen resolution and the length of the time series, it is difficult to analyze the RP only by means of visual inspection (which is anyway useful to detect, e.g. simple non stationarities). To cope with this problem, Zbilut and Webber [3] introduced the quantification of the structures present in the RP.

Starting from the distribution of the diagonal lines length \( P(l) \), one can compute several indicators, the most important of which are the Recurrence Rate \( RR \), the Determinism \( DET \), the Entropy \( ENT \) and the average line length \( < L > \), defined as [2]:

\[
RR = \frac{1}{N^2} \sum_{i,j} R_{ij} = \frac{1}{N^2} \sum_{l=1}^{N} lP(l), \quad DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)}, \quad ENT = -\sum_{l=l_{min}}^{N} p(l) \log p(l), \quad < L > = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=l_{min}}^{N} P(l)},
\]

The Recurrence Rate, \( RR \), represents the fraction of recurrent points with respect to the total number of possible recurrences. \( DET \) is the fraction of recurrent points forming diagonal structures with a minimum length \( l_{min} \) with respect to all the recurrences (a line of length \( l \) indicates that, for \( l \) time steps, the trajectory in the phase space visits the same region at different times). \( DET \) provides a measure of the predictability of the system, because it accounts for the diagonal structures in the RP. High values of \( DET \) mean that the recurrence points are mainly organized in diagonal lines. \( < L > \) and \( ENT \) are defined as:

\[
ENT = -\sum_{l=l_{min}}^{N} p(l) \log p(l), \quad < L > = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=l_{min}}^{N} P(l)}, \quad ENT
\]

where \( p(l) = \frac{P(l)}{\sum_{l=l_{min}}^{N} P(l)} \). \( ENT \) is a complexity measure of the distribution of the diagonal lines in the RP. It refers to the Shannon entropy with respect to the probability of finding a diagonal line of exactly length \( l \). Finally, \( < L > \) indicates the average line length present in the RP.

**EXPERIMENTAL DATA**

Three subjects affected by pulmonary emphysema (subject 1), hypersensitivity pneumonia (subject 2) and idiopathic pulmonary fibrosis (subject 3) are considered. A further normal subject is considered as a baseline case. The data set consists of 6 breaths for subject 1 and the normal case, and 4 breaths for subjects 2 and 3. The time series have been
FIGURE 1. The analyzed signals and their power spectral density. Panels (a-b): subject 1 (pulmonary emphysema), panels (c-d): subject 2 (Hypersensitivity pneumonia), panels (e-f): subject 3 (idiopathic pulmonary fibrosis), and panels (g-h): normal subject. On the left column, the blue lines correspond to the lung sounds, the red lines refer to the airflow. The PSDs of the right column show only slight differences in the spectral content of the signal.

The inspiration phase of every breath of each subject has been analyzed by means of the Recurrence Quantification Analysis and power spectral density (PSD). Figure 1 shows the time series and PSD of the analyzed signals. Panels (a-b) refer to subject 1, (c-d) to Subject 2, (e-f) to Subject 3, and finally (g-h) to the normal case. The plots on the left column show the amplitude of the lung sound (blue line) and the airflow (red line). Inspiration produces a negative flow, while expiration a positive one. The right column shows the Power Spectral Density of the signals. As one can notice, only slight differences characterize the power spectra of the three subjects, while a slightly modified shape is observed in the normal case (notice the small peak in $f \sim 1800$ Hz). Before applying the RQA, the time series have been embedded in a phase space of dimension $D - E = 3$ (computed by means of the false nearest neighbor method [1]) and delay time $\tau = 20$, corresponding to the first minimum of the autocorrelation function. After the embedding, in order to not introduce biases in the RQA parameters, the threshold $\epsilon$ was chosen in order to obtain a recurrence rate $RR \sim 5\%$, guaranteeing that the recurrence plots have almost the same density. The parameters used are the mean diagonal line length $< L >$, the determinism $DET$, and the entropy $ENT$. 

recorded by means of air-coupled condenser microphone equipped with a 16 bit A/D converter and are sampled at 8195 Hz. The sensor is positioned on the posterior middle zone of the chest.

ANALYSIS AND RESULTS

The inspiration phase of every breath of each subject has been analyzed by means of the Recurrence Quantification Analysis and power spectral density (PSD). Figure 1 shows the time series and PSD of the analyzed signals. Panels (a-b) refer to subject 1, (c-d) to Subject 2, (e-f) to Subject 3, and finally (g-h) to the normal case. The plots on the left column show the amplitude of the lung sound (blue line) and the airflow (red line). Inspiration produces a negative flow, while expiration a positive one. The right column shows the Power Spectral Density of the signals. As one can notice, only slight differences characterize the power spectra of the three subjects, while a slightly modified shape is observed in the normal case (notice the small peak in $f \sim 1800$ Hz). Before applying the RQA, the time series have been embedded in a phase space of dimension $D - E = 3$ (computed by means of the false nearest neighbor method [1]) and delay time $\tau = 20$, corresponding to the first minimum of the autocorrelation function. After the embedding, in order to not introduce biases in the RQA parameters, the threshold $\epsilon$ was chosen in order to obtain a recurrence rate $RR \sim 5\%$, guaranteeing that the recurrence plots have almost the same density. The parameters used are the mean diagonal line length $< L >$, the determinism $DET$, and the entropy $ENT$. 

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FIGURE 2. Position of the inspiration phases of the breaths in the \((DET, ENT, <L>)\) diagram.

Figure 2 shows the position of the breaths in the inspiration phase in the space \((DET, ENT, <L>)\). As one can notice, the clusters relative to all subjects are clearly separated, and the normal subject is positioned in the central part of the diagram. It is worth noticing that, under the clinical point of view, subjects 2 and 3 are clearly separated. This apparently does not reflect the fact that in the two pathologies the damage is localized in the same region, the pulmonary interstitium. Actually, the two subjects showed different responses to the steroid therapy: in particular, subject 2 responded positively, while subject 3 was insensitive to the therapy.

CONCLUSIONS

By means of methods borrowed from the nonlinear time series analysis, namely the RQA, we have characterized and classified breaths coming from different lung diseases. The \((DET, ENT, <L>)\) diagram allowed for a reliable separation of the three pathologies and the normal case. It is worth noticing that the separation of subjects 2 and 3 indicates important clinical issues. The analysis provided quantitative measures useful in the clinical, diagnostic and follow up phases. Furthermore, it is based on non invasive and easily repeatable examinations.

Future work will be devoted to the application of this promising analysis to a larger database.

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