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Technical Note

A chaotic viewpoint on noise reduction from respiratory sounds

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ABSTRACT

Analysis of respiratory sounds can help the recognition of various respiratory diseases. Due to acoustic noise in hospital environments, the recorded sounds are polluted. The noise can destroy the analysis and should therefore be removed. Because of the chaotic nature of respiratory sounds, traditional noise reduction methods may not be efficient. Thus taking advantage of algorithms especially devised for noise reduction from chaotic signals can lead to better results. In this paper, a new method based on an original local projection algorithm is presented to reduce the noise in respiratory sounds.

1. Introduction

Processing of breath sounds is of great interest to scientists owing to their diagnostic value in airway and lung diseases and determination of critical conditions in operating rooms. However, because of environmental noise in operating and emergency rooms from surgical devices, ventilation machines, conversation, alarms, etc., it is impossible to achieve recorded respiratory sounds without ambient noise [1]. Such noise destroys the features, and progressively decreases the accuracy of recognition in environments with low signal to noise ratio (SNR) [2]. In other words, to recognize the respiratory diseases using breath sounds, clean sounds are required. Hence the noise should be removed from recorded respiratory signals.

In Ref. [3], respiratory sounds were investigated from the chaotic viewpoint, and indicators such as Lyapunov exponent, correlation dimension (D_2) and Kaplan–Yorke (D_{KY}) dimension were calculated for respiratory sounds. From investigation of sixteen healthy subjects, it was shown for all the subjects that the sum of the Lyapunov exponents was negative, and the largest exponent was positive. Furthermore, D_2 and D_{KY} were fractal for all the subjects. Consequently, breath sounds appear chaotic. Chaotic signals are random-like in the time domain, and are wide-band in the frequency domain [4], which makes conventional signal processing methods and linear methods inappropriate for noise reduction from these signals. Thus in this work, a new method is proposed for noise reduction based on the chaotic nature of respiratory sounds. In the proposed method, which is similar to many other studies in this field, it is assumed that the clean part of the chaotic data (the respiratory sound) is well-behaved. However, due to noise effects, the real dynamic behavior is concealed.

It is assumed that Gaussian white noise has been added to the main clean signal [2,4]. No other information about the clean signal is assumed other than that mentioned above.

The electret microphones or sensitive contact accelerometers are often used to record respiratory sounds. After recording, these sounds are amplified, and after noise cancelation using signal processing methods to recognize the respiratory diseases, the features are extracted [5].

Respiratory sounds are divided into two groups: normal and abnormal sounds. Normal breath sounds are heard from the top of the different parts of the chest wall in healthy subjects, while abnormal respiratory sounds are heard from different parts of the chest wall in subjects with different respiratory diseases [6]. Some of these abnormal sounds are: *wheezes* heard in case of airway narrowing and increase in secretions, *stridors* which are heard when a partial obstruction occurs in a central airway especially near the larynx (this sound is similar to a wheeze; however, it is usually heard in inspiration, whereas wheeze is heard in expiration), *crackles* which are usually produced as a result of airway opening and airway secretion and are divided into the two groups of fine crackles and coarse crackles, *squawks* which are caused by explosive opening and vibration of the unstable airways, and finally *friction rub* which is heard in the location where the lungs meet and is caused

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by the contact of coarsened pleural surfaces together which occurs smoothly and silently under normal conditions [5]. Furthermore, both of these two groups of sounds have different features depending on recording location on the chest wall. In this study, noise reduction has been accomplished by the proposed algorithm for different kinds of the breath sounds including normal and abnormal sounds. The respiratory sounds used in this study are taken from [7]. Then, Gaussian white noise with a 10 dB SNR is added to them, and finally, noise reduction is performed through the proposed algorithm. The results show that the proposed method is efficient for noise reduction from both normal and abnormal respiratory sounds.

The method proposed in this work has been exclusively devised for the type of continuous chaotic signals (flows) corresponding to respiratory sounds. In particular, the algorithm has been designed based on the geometric features of a continuous chaotic signal in phase space. In the proposed algorithm, a one-dimensional chaotic time series is embedded in a high dimensional phase space. After reconstruction of the phase space, unlike the Local Projection (LP) method which performs linear estimation of the trajectory in each local region, in this method, an n-degree curve is used for local estimation, where n is selected adaptively. In fact, a mechanism has been designed which determines the appropriate curve degree in each region based on geometric features of the trajectory and its stretching and folding. In this way, flexibility of the algorithm and its ability to reduce error is improved.

In Ref. [8] using an adaptive filter, and in Ref. [9] employing the dual sensor spectral subtraction method, the environmental noise was reduced relative to the breath sounds. Both of these methods require a reference signal. However, such a signal is not always available. Since the proposed method does not require any reference signal for noise reduction, a fair comparison requires methods that also do not require a reference signal. Thus the proposed method is compared with a frequency filtered (50–2500 Hz bandwidth) [5] ALE algorithm using an adaptive filter (which uses the delayed noisy signal as the reference signal and does not need other signals as a reference), and the LP method. The results of this comparison show superior efficiency of the new method in noise reduction from respiratory sounds.

In Section 2, the algorithm is explained. In Section 3, the simulation results and comparison with other algorithms are presented. Section 4 is provides discussion and conclusion.

2. Proposed algorithm

Since our algorithm is a modification of the LP method, this method is briefly described.

2.1. LP algorithm

A deterministic chaotic flow is a set of states resulting from the integration of $\overrightarrow{\dot{x}(t)} = f(\overrightarrow{x(t)})$ over time. Usually, $\overrightarrow{x(t)} = (x_1(t), x_2(t), \ldots, x_i(t), \ldots x_m(t))$ is indirectly measured in discrete time intervals transformed by some measurement function $\vec{h}(\overrightarrow{x(t)})$ [10].

Assume that only a single scalar value, s_k, from the vector $\vec{x}$ is measured at each time, and this value is affected by noise $N(k\delta t)$. Therefore, the measured scalar, s_k, is:

$$s_k = h(x_i(k\delta t)) + N(k\delta t)) \tag{1}$$

The LP method involves projection of the measured trajectories onto an attractor with low-dimension. This task is performed because the chaotic data must be limited to a chaotic attractor with a certain dimension, and any divergence from this attractor is caused by noise. Therefore, in noise reduction, the attractor is estimated locally by a tangent plane that is determined using principle component analysis [11]. The noisy trajectory is projected to an attractor using noise reduction, which is similar to a local one-degree estimation of the trajectory phase space structure. Therefore for each point, a local neighborhood is determined including the points on the trajectory in the vicinity of that point. For this set of points, a linear plane is estimated, and the considered point is projected onto that plane.

For more details see Ref. [4].

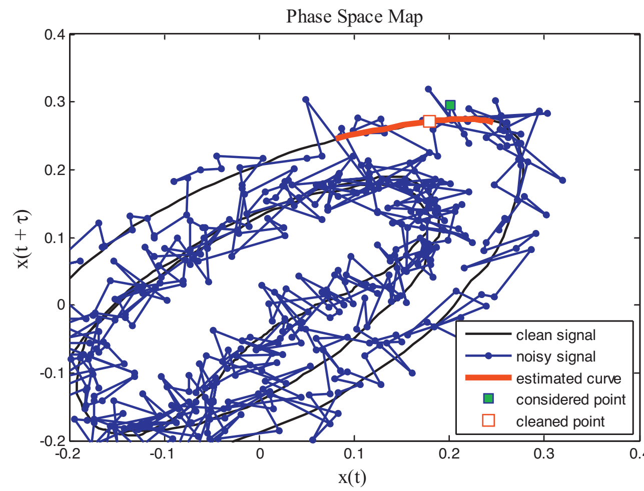

Fig. 1. Clean trajectory (black curve) and noisy trajectory (blue curve). The proposed algorithm estimates a curve (red curve) between the noisy points around a considered point (green square), and then projects that point onto its corresponding point on the estimated curve (white square). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Proposed algorithm

In this algorithm, unlike the LP method, the trajectory points are projected onto an n-degree curve (in this work n is 3 or 4), instead of projecting data onto a one-degree plane in the phase space. The considered curve is determined by this equation:

$$\begin{aligned} y(t) &= (y_1(t), y_2(t), \ldots, y_m(t)) \\ &= \big((a_{n1}t^n + a_{(n-1)1}t^{n-1} + \ldots + a_{01}), \\ &\quad ((a_{n2}t^n + a_{(n-1)2}t^{n-1} + \ldots + a_{02}), \ldots, \\ &\quad (a_{nm}t^n + a_{(n-1)m}t^{n-1} + \ldots + a_{0m}\big) \end{aligned} \tag{2}$$

To modify each point $((\vec{s^*} = \overrightarrow{s(t^*)}))$ of the noisy trajectory in the phase space, a neighborhood with $N_{\text{neighbor}} = 2N_1 + 1$ points is considered close to the considered point which includes that point $(\vec{s^*})$ as well. Since a continuous chaotic time series is investigated in this study, determination of the neighboring points is not difficult because in continuous signals, the neighboring points in the phase space are neighbors in time too. Thus in each neighborhood, N1 points before the considered point and N1 points after it are considered as its neighbors. Then in each neighborhood using the least square algorithm, aij coefficients, where $\{i = n, n-1, \ldots, 0\}$ and $\{j = 1, 2, \ldots, m\}$, are determined in a way that the $\vec{y}$ curve passes through these points with the least square error. In the next step, the considered point is projected onto the achieved curve (in order to replace it with the corresponding point on the achieved curve. Since the considered point is the middle of the neighboring points, it is the middle point on the fitted n-degree curve as well [12] (Fig. 1)).

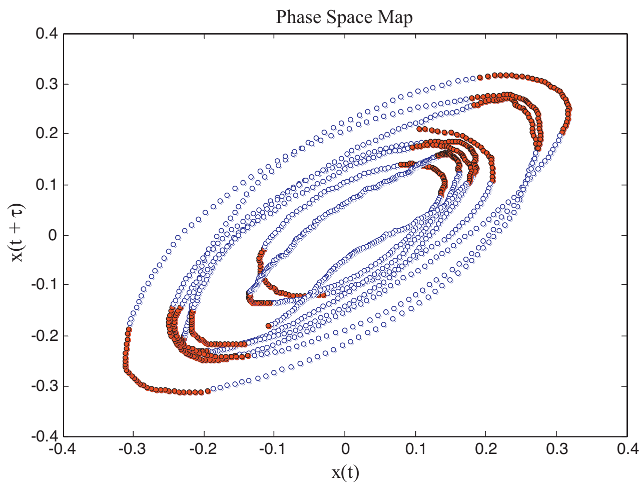

Fig. 2. Stretching and folding points for a part of the tracheal sound. The stretching points of the trajectory are presented by blue circles, and the folding points are marked by solid red circles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

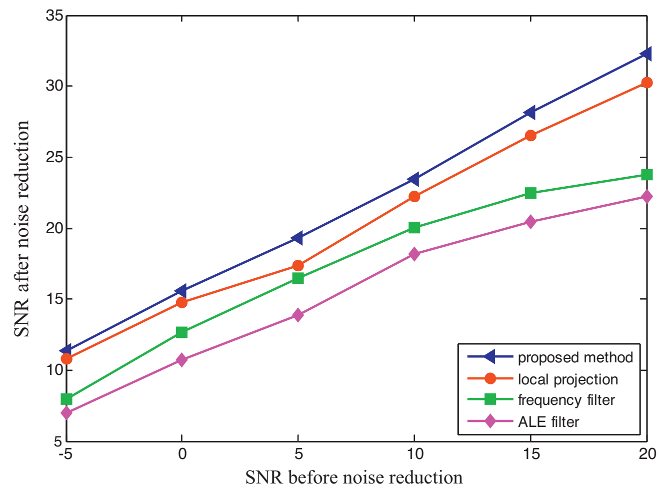

Fig. 3. Comparison of the different mentioned methods with the proposed algorithm. The plot shows for all input SNRs, the mean of the output SNRs of the proposed algorithm is higher than the other methods.

In this method after implementation of the algorithm on all the trajectory points once, the noise is reduced. However, the algorithm has can be successively implemented, which results in a smoother final trajectory with a lower error level [12]. (It is obvious that the error is higher for the several points in the extremities of the trajectory, because the number of neighbors is reduced.)

2.3. Stretching and folding

An important feature of a chaotic trajectory is stretching and folding [13]. In the proposed algorithm as explained above, the location of each point in the phase space is modified through projection of that point onto the curve passing through its neighborhood. Another significant issue in this algorithm is selection of the appropriate curve in every neighborhood. The idea employed here is choosing curves with low curvature for the stretching points of the trajectory (one-degree and more appropriate three-degree) and choosing curves with high curvature for the folding points where the direction of the trajectory suddenly changes (two or four degrees). Therefore, a criterion is required to measure the stretching and folding. It is evident that near the folding point, the curvature in the trajectory is higher.

The curvature of a curve such as $R(t) = (r_1(t), r_2(t), \ldots, r_m(t))$ is calculated using the following equation [14]:

$$\kappa(t) = |\dot{\vec{R}} \times \ddot{\vec{R}}| / |\dot{\vec{R}}|^3 \tag{3}$$

Although for clean signals, this equation determines the curvature well, numerical methods have problems calculating the curvature; especially the presence of the $|\dot{R}|^3$ term in the denominator since $|\dot{R}|$ approaching zero introduces obstacles. Therefore, we used another method to determine the curvature at each point, where the curvature is calculated as the angle between the vector connecting that point to the next point and vector connecting the previous point to that point in phase space. However, the noise impedes accurate curvature determination. Moreover, in order to solve this problem, the proposed noise reduction algorithm is first implemented with $n = 1$ (similar to the LP method). In this way, although the achieved trajectory may have more error in comparison with the original trajectory, its geometric form is similar to the actual trajectory. In fact, wherever the curvature in the original trajectory is high, the achieved curvature for the estimated trajectory is also high, and vice versa. Thus, the accurate curvature at each point is determined from the achieved trajectory. Then through

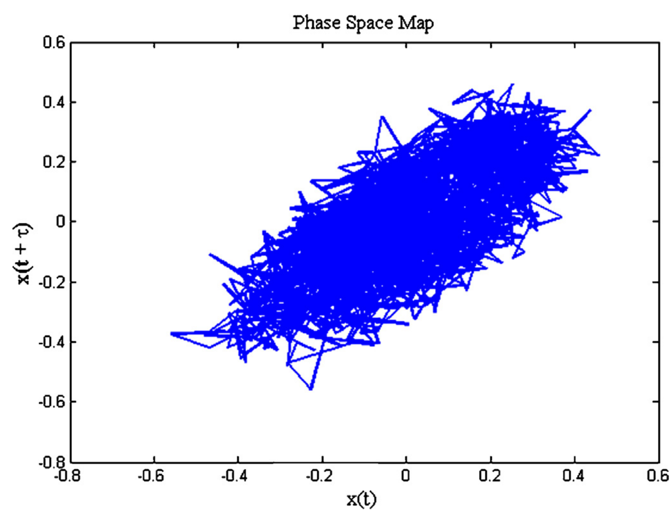

Fig. 4. The phase space plot for a part of the noisy tracheal sound.

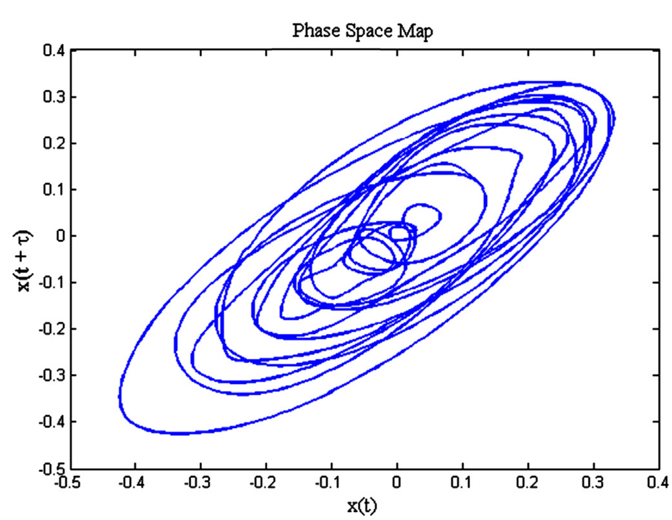

Fig. 5. The phase space plot for a part of the filtered tracheal sound.

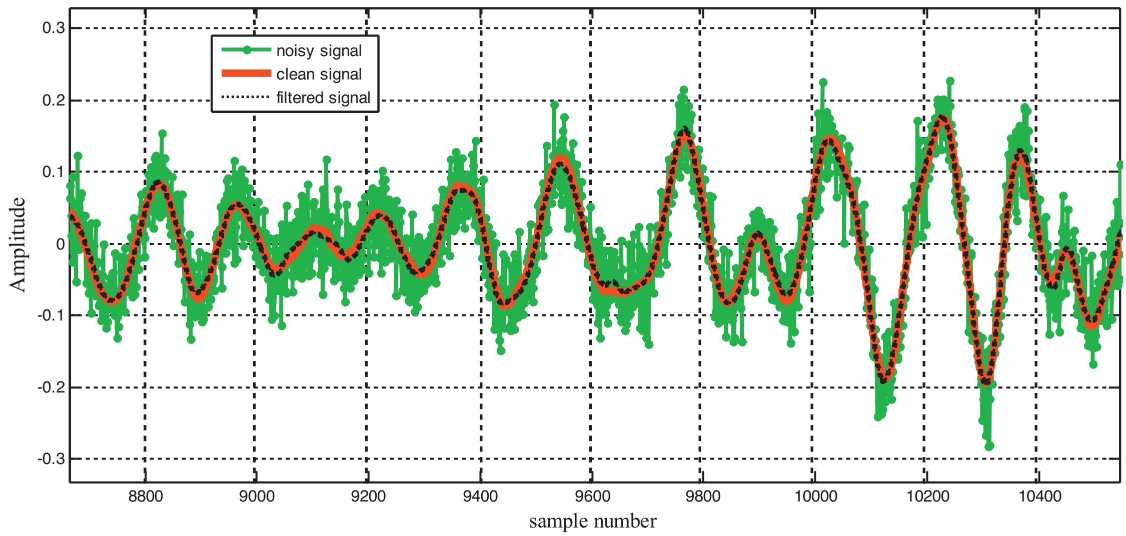

Fig. 6. A part of a typical clean normal breath sound (red curve), a signal polluted by the noise (green circle-curve), and the sound filtered by the proposed algorithm (dashed-black curve). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

determination of the maximum and minimum of the achieved curvature, the interval between them is divided into two sections. For high curvatures, four-degree curves, and for low curvatures, three-degree curves are employed [12].

In Fig. 2, the points corresponding to the maximum and minimum curvature of a part of the trajectory of tracheal sounds are presented. In this figure, the solid red circles correspond to regions with high curvature (folding points), and the blue circles represent regions with low curvature (stretching points).

3. Simulation and results

In this section, the efficiency of the proposed method is investigated. The proposed algorithm is applied to the twenty different breath sounds in [7] which includes normal and abnormal respiratory sounds. The investigated normal breath sounds include tracheal, bronchovesicular, and bronchial. The abnormal breath sounds include wheezing as heard in asthma, emphysema, pneumonia, congestive heart failure, chronic bronchitis and bronchiectasis diseases [15], stridor sound which is a special kind of wheeze and is heard in patients with tracheal or laryngeal obstruction [15], and fine crackle sound which is heard in heart congestion failure, bronchiectasis, pneumonia, and pulmonary fibrosis [5]. White Gaussian noise with 10 dB SNR has been added to these sounds. Then, this noise is reduced with the proposed algorithm and with the other mentioned methods. The mean of the output signal SNRs for the proposed algorithm, the LP method, ALE and frequency filter with 50–2500 Hz bandwidth are provided in Table 1.

As illustrated in Table 1, the proposed method has reduced the noise from breath sounds more efficiently than the other methods, and for different kinds of the breath sounds such as normal and abnormal, its output SNR is higher than the others. In Fig. 3, the efficiency of the different methods on some abnormal breath sounds is compared, showing the superiority of the proposed method.

Table 1
Mean of the output SNRs of the proposed algorithm and other comparison methods for the twenty different normal and abnormal breath sounds.

Respiratory sound	ALE filter	Frequency filter	LP	Proposed method
Wheeze	16.8244	19.6233	21.9983	22.9801
Stridor	16.8497	20.4861	22.6582	23.4346
crackle	16.0980	18.5648	21.6186	22.6479
Tracheal	14.2606	14.7717	19.3846	20.6731
Bronchial	13.9565	14.4430	19.1420	20.2756
Bronchovesicular	17.6877	19.1421	22.2131	23.8961

A phase space plot of the noisy and denoised signals using the proposed method for a part of the tracheal sound is illustrated in Figs. 4 and 5.

Fig. 6 shows a part of a typical clean lung sound, a lung sound polluted with the noise, and the sound filtered by the proposed algorithm. The noise is almost completely removed.

4. Conclusion

When respiratory sounds are recorded in surgical or emergency rooms to recognize respiratory diseases and detect critical conditions, the acoustic noise in the environment is mingled with these sounds. In this paper, a new method is presented for reducing noise that is based on the chaotic dynamic of breath sounds. Indeed, the proposed method is a modification of the LP algorithm. In this algorithm, in order to locally estimate the trajectory in the phase space, flexible curves were employed with three or four degrees instead of the line. Since stretching and folding is an important feature of chaotic signals, based on this feature a new adaptive method is proposed to select the appropriate curve in every piece of the trajectory. By this method, the regions with low curvature have been used for the stretching points (three-degree in this work), and the curves with higher curvature have been used in folding points of the trajectory (four-degree). Noise reduction with the proposed algorithm, the LP method, the Adaptive Line Enhancement filter, and the frequency filter with 50–2500 Hz bandwidth were performed for different kinds of the respiratory sounds such as normal and abnormal sounds. The comparison of these methods shows that the proposed algorithm reduces the environmental noise from different breath sounds more efficiency than the other mentioned methods over the whole range of input SNRs.

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