SEARCHING FOR NONLINEAR RELATIONS IN WHITENED JITTER TIME SERIES

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ABSTRACT

Even in sustained vowels, durations of successive glottal cycles are not identical. They fluctuate quasi-randomly around an average. This phenomenon is known as jitter. More recently, correlation analysis has shown that perturbations of neighboring glottal cycles are interdependent, i.e. they are not purely random. We have shown that the non-random component of jitter can be modeled by means of a linear auto-regressive time series model which absorbs correlations between fluctuations of adjacent cycles and leaves a purely random component. The problem here is that nonlinear relations may be missed by correlation analysis or linear auto-regressive modeling. Nonlinear relations could be the signature of chaotic vibratory patterns which some authors expect for some pathological conditions of the vocal folds. We therefore decided to search inside whitened jitter time series (i.e. time series from which any linear correlations had been removed) for nonlinear or other anomalous dependencies between neighboring cycles. The results showed the following. Of the 265 time series, 231 appeared to have been correctly represented by linear auto-regressive models. For 29 series, out of the 34 remaining, deviations from pure randomness could be traced to isolated anomalous glottal cycles which statistical time series models had not taken into account. Finally, five signals, produced by three speakers, were detected which displayed relations between neighboring cycles which could not be traced either to linear correlations or to isolated glitches.

1. INTRODUCTION

Jitter is the small interval-to-interval fluctuations of glottal cycle lengths and since it is believed to be able to acoustically reveal pathological vibratory patterns in the vocal folds it has been studied over the last thirty years. A superficial examination of a sequence of cycle perturbations would suggest that these are random, i.e. randomly drawn from a population described by means of its statistical distribution. However, correlation analysis has revealed that these cycle length perturbations tend to vary together in a way not expected on the basis of chance alone. We therefore propose representing jitter by means of a linear auto-regressive time series model (1) which has the following form [1].

$$P_i-\langle P\rangle = a_1(P_{i-1}-\langle P\rangle) + a_2(P_{i-2}-\langle P\rangle) + a_3(P_{i-3}-\langle P\rangle) + .. + a_M(P_{i-M}-\langle P\rangle) + Z_i \qquad (1)$$

$P_i-\langle P\rangle$ is the perturbation of the ith cycle with reference to the average cycle length $\langle P\rangle$, model coefficients a_j weight the impact of past on present perturbations, M is the order of the model; and Z_i is the residue. Order M and coefficients a_j are calculated for a given jitter time series by means of conventional linear methods [2]. Residue Z is obtained by subtracting the right-hand side from the left-hand side of expression (1).

When the previous model is an adequate representation of a given jitter time series residue Z is decorrelated, i.e. its spectral envelope is flat. The problem is that relations in jitter time series $P_i-\langle P\rangle$ must be linear in order that residue Z can be assumed to be random. When this assumption is not true, i.e. when inter-relations between neighbouring perturbations are nonlinear or when anomalies occur that cannot be accounted for by model (1), then residue Z may not be a random series even though any statistically significant linear correlations have been removed.

Searching in residue Z for any remaining relations between samples would therefore be a means of testing the relevance of model (1). This search would have to be carried out via methods other than conventional correlation analysis since linear correlations have been removed from residue Z by means of the weighted sum of model (1) [3]. Also, this search would be a means of investigating the conjecture, put forward by several authors, that some conditions of the larynx give rise to chaotic vibrations of the vocal folds [4]. Indeed, nonlinear relations may be the signature of chaotic oscillations whereas linear relations are not. Chaos is the state in which a dynamical system finds itself when its movement is pseudo-random, i.e. deterministic but not predictable in the long term [5].

2. METHODS

2.1. Corpus

The corpus was comprised of 265 jitter time series obtained from 265 vocoïds [a] [i] [u] sustained by 38 healthy and 45 dysphonic speakers. Model (1) was fitted to each time series and residue Z calculated by subtraction. Each cycle length time series successfully passed the following tests: Hess's test for bias due to interpolation — interpolation was used to measure cycle lengths with a precision of 6.25 microseconds [6]; an intercorrelation test of acoustic and electroglottographic time series, test which revealed contamination by aerodynamic or measurement noise; a student's t-test for model order M and three correlation tests for the whiteness (i.e. absence of linear correlations) of residue Z [1] [6].

2.2. Search for nonlinear relations between samples of residue Z

Once the jitter time series were statistically free of linear inter-dependencies between neighbouring cycle perturbations, i. e. raw jitter P_i-<P> had been replaced by residue Z_i, the search for any remaining nonlinear anomalies had to be carried out via procedures other than conventional correlation analysis. We made use of four semi-quantitative methods, three of which are known to have been employed for detecting chaos in time series [8]. Before, all the residue time series were normalized, so that their variances were equal to one and their averages equal to zero.

The first method consisted of displaying present and antecedent samples of residue Z within a bi-dimensional graph. It is known that, within such a display, a purely random and normalized time series gives rise to a shapeless blob of data points centered on the origin of the axes of the graph. Any detectable pattern would point to relations between cycle perturbations [5].

The second method was based on an iterated function system [8]. Since the results showed that, generally speaking, the samples in the perturbation time series were too few to give rise to meaningful patterns in this plot, we will not discuss them any further here.

The third method was close pair analysis by means of a recurrence plot [5]. The recipe was the following. As a first step, all the data of the residue time series Z were combined two by two so as to form all possible pairs. As a second step, the Euclidean intra-pair distances were computed. A threshold was then chosen and, as a third step, the differences were noted which were less than this critical value. In our case, the threshold was fixed at 0.1. A way to depict the information so gained was to make a plot in which the horizontal axis displayed the label in the time series of the first datum and the vertical axis the label of the second datum of each pair. A point was plotted at the intersection of the labels when two consecutive intra-pair differences were below the critical threshold. Generally speaking, chaotic time series were expected to give rise to longer strings of points parallel to the diagonal than white noise, the reason being the presence of nonlinear correlations in the case of chaos.

A fourth method displayed the time series data after the polar transformation proposed by Pickover, which projected the time series data onto a two-dimensional plot and artificially symmetrized the display [9]. These symmetries were meaningless as far as relations between time series samples were concerned. Their raison d'être was that people visually compare patterned displays more easily than featureless blobs of data points.

These four methods gave rise to two-dimensional displays which made visible those between-data relations that could not be tracked by conventional linear correlation analysis. The problem was that these plots were pictures only which did not gauge the statistical or practical relevance of differences between time series so observed.

In order to be able to appraise the relevance of differences between plots, we defined features that quantitatively characterised the displays and ascertained their statistical significance by means of randomisation. Indeed, we randomly scrambled the whitened jitter time series and computed the same features for the scrambled and unscrambled plots. Since random scrambling destroyed any relations between time series data, the values of the features of the original, unscrambled time series were expected to be exceptional when relations between data existed, and unexceptional when there were none. We scrambled each time series 100 times. When the observed unscrambled feature values were atypical compared to the "scrambled" feature values we rejected the zero hypothesis that no relations - as measured by means of the features - between data points were present. In practice, taking into account the kind of characteristics that we made use of, we rejected the zero hypothesis when the feature values of the observed time series were bigger than the feature values of more than 95 out of 100 scrambled time series.

Because of lack of space we are presenting the recurrence plot-based features only. Conventionally, they have been defined as the number of consecutive doublets, triplets, quadruplets and quintuplets of sample pairs whose intra-pair distances were below the critical threshold [5]. "Consecutive" here means that a pair (s_i,s_j) was followed by a pair (s_{i+1}, s_{j+1}), with i and j being the indices of any two time series samples. For example, the so-defined feature of a typical time series was equal to (38, 3, 0, 0). This means that the intra-pair distances were less than the critical threshold for 38 doublets, 3 triplets and 0 quadruplets and quintuplets of consecutive pairs. The corresponding average feature computed for the 100 scrambled time series was equal to (41, 2, 0, 0). Counting indicated that the 100 scrambled time series gave rise respectively 70, 28, 14 and 0 times to a greater number of doublets, triplets, quadruplets and quintuplets than the ones observed. This demonstrates that the observed time series did not display any special relations between any two samples. Indeed, the decision to reject the zero hypothesis was based on the doublets and triplets that are the most numerous in the time series observed.

3. RESULTS AND DISCUSSION

The results are as follows. Out of 265 jitter time series, 34 were exceptional in the above sense, i.e. less than five out of one hundred scrambled time series gave rise to a greater number of n-tuplets of below-threshold intra-pair distances than the unscrambled time series observed.

Of these 34 anomalous time series, 29 were either statistical flukes, i. e. their statistical exceptionality disappeared when the randomisations were relaunched, or the effect of outliers. Indeed, it must not be forgotten that time series Z had been normalized. As a consequence, when one or several samples with exceptionally high values were present in the time series, the values of the more typical samples were compressed. Although scrambling only modified the order of the time series data and not their values, outliers might nevertheless give rise to slightly anomalous recurrence plots when more than one outlier existed and when they clustered together. Also, these 29 time series were atypical only in the number of their doublets. The number of higher-order n-tuplets was unexceptional.

Finally, 5 out of the 34 exceptional time series were noteworthy to the extent that the number of doublets and triplets in the unscrambled (i.e. observed) recurrence plots was very different from the scrambled (i.e. control) plots. They gave rise to Pickover, recurrence and present/antecedent plots that showed patterns that were invisible to the conventional correlation analysis of residue Z and which were not due to outliers, trends or cyclic components.

It would be premature to conclude that these five exceptional jitter patterns were the signature of chaos. As far as we can judge, the important result was that 231 out of 265 jitter time series did not exhibit any patterns at all and that 29 out of the 34 remaining series gave rise to patterns that could be traced to outliers. Indeed, outliers in residue Z were signs of local failures on the part of model (1) to represent jitter time series adequately. Inspection revealed that these failures were usually due to local infringements of the hypothesis of stationarity, but that they were not marked or numerous enough to be revealed by a conventional correlation analysis of residue Z. While it is mathematically true that it is not possible to prove that a time series is random, both the present tests and the previous linear correlation tests of residue Z suggest that the great majority of jitter time series can be described by means of a linear statistical time series model. This would exclude the possibility of chaos underlying these series. This means that if chaotic vocal fold vibrations exist, they are rare or confined to exceptional laryngeal conditions.

Figure 1 shows the present/antecedent plot (Z_i, Z_{i-1}) of a typical, normalized jitter time series Z without any visible pattern. This kind of display is illustrative of the vast majority of our time series. Figures 2 to 6 show the present/antecedent plots of the five statistically exceptional jitter time series detected by means of their recurrence plots. Figures 2 to 4 display the jitter data of three vocoïds [a] [i] [u] sustained by the same healthy female speaker. Figure 5 is the display of a similar pattern produced by a dysphonic male speaker without any precise diagnosis, but whose voice had been described as husky in the anamnesis. Finally, Figure 6 shows an oblique T-shaped pattern of the whitened jitter of an ENT-patient diagnosed as suffering from pharyngitis and slight laryngitis.

4. REFERENCES

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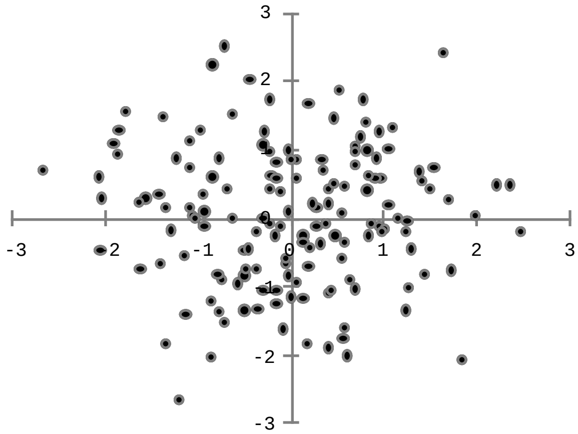
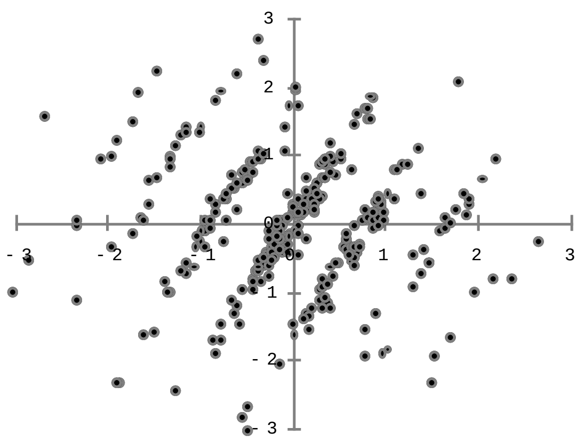


Figure 1



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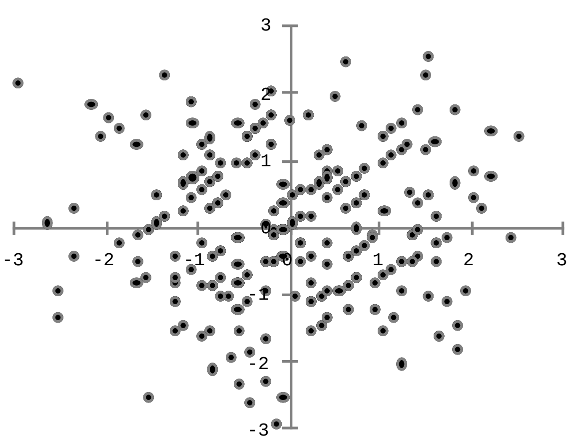
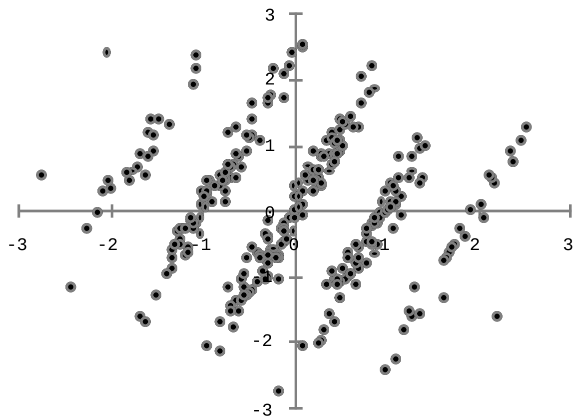


Figure 3



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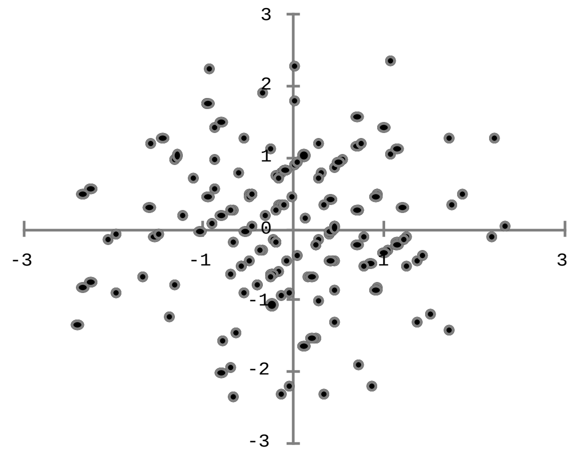

Figure 5

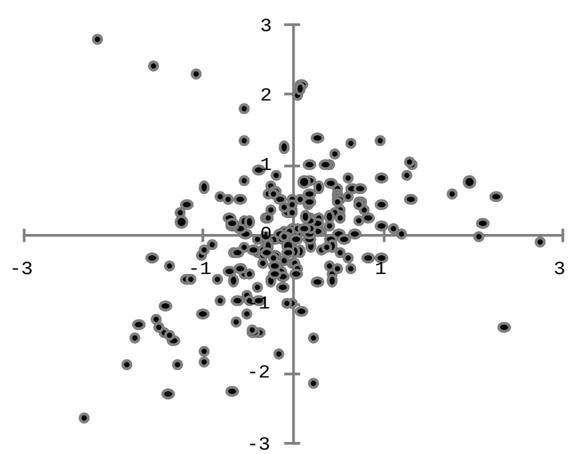

Figure 6