IDENTIFYING LARYNGEAL ATTRACTOR CHANGES FROM PERIODICITY DIAGRAMS

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ABSTRACT

A technique to find repetitions in a laryngeal signal such as the volume velocity seems to identify the moments at which the larynx changes mode. The technique is based on the "close-returns plots" that have been used in the past. Pictures derived from the technique may help identify the segments when the laryngeal dynamics are confined to one attractor, a necessary condition for most nonlinear-dynamics processing. The technique appears equally useful for identifying such attractor changes in any nonlinear dynamical flow.

1. MOTIVATION AND INTRODUCTION

We are studying the application of techniques from nonlinear dynamics (NLD) to the analysis of voice. We hope that the concepts and quantities relevant to NLD will describe voice disorders better than those relevant to statistics have. [Ludlow *et al.*, 1987] For example, the negative Lyapunov exponents [Peitgen *et al.*, 1992; Titze *et al.*, 1993; Abarbanel, 1996] measure energy dissipation rates in laryngeal motion. In a prolonged vowel ("say 'aaah'"), we might find that these exponents correlate with tissue pathologies such as edema or atrophy, simply because of the role that the tissues play in dissipation.

Most NLD techniques that provide numerical measures such as the exponents require that the system remain in or near (and converge to) a single attractor. (The measures are, in fact, parameters specific to an attractor.) In ideal cases, the familiar laryngeal phonation registers (normal, falsetto, and pulse) may identify distinct attractors; in practice, these labels probably often ignore certain subtler distinctions.

As we will see, the larynx may experience several changes of attractor in a prolonged phonation (~1 sec). Although it has proved possible in earlier work to extract consistent estimates of Lyapunov exponents over much shorter times, it is important to apply the analysis only to a single attractor at a time. But how can we know if the dynamics has changed, and how can anyone hope to notice, either quickly or without long training?

2. ATTRACTORS FOR THE LARYNX

Fortunately, attractors are qualitative features of the dynamics, so we can presume the larynx to move under the influence of a single attractor at least for short intervals. Unfortunately, it is not always easy to verify that the laryngeal dynamics has remained in one attractor, especially without detailed inspection of the waveform of the acoustic or other signal we have collected.

Worse, if the motion is far from periodic, it may be difficult to detect changes even by inspecting the waveform visually (or acoustically/spectrographically) – especially in the presence of noise. Qualitative changes in a biphonation,[1] such as a period-doubling of *one* of the "fundamental" frequencies due to a small but critical change in muscular tension, may be too subtle to notice in an already complicated signal. If the dynamics is already deterministically chaotic, this is almost certainly true, since the waveform cannot show any long-range predictability and its spectrum, even without noise, cannot be not discrete.

3. PERIODIC ORBITS IN ATTRACTORS

Periodic orbits are a critical feature of virtually *all* attractors – chaotic and otherwise.[2]

[1] Characterized by two independent "fundamental" frequencies. The term is sometimes recommended [H.Herzel, pers.comm.; I.Titze, pers.comm.] over the more conventional *diplophonia* in order to avoid confusion with period-doubling (occurrence of the first subharmonic).

[2] We omit consideration of point attractors – those in which the system state is merely a constant, such as the

Specifically, if an orbit follows an attractor and is not chaotic, then it must consist of a finite set of periodic components, typically (for the larynx) just one or two. Insofar as one component is dominant, we will directly observe close (or perfect) returns of the system to a state it occupied one, two, three, ... periods earlier.

Conversely, if the orbit is chaotic, then it will *almost always* be found following some periodic orbit, but only temporarily.[3] As the orbit continues, it will diverge from the periodic orbit (typically, its period will change, slowly at first), until we observe it under the "influence" of some other periodic orbit, perhaps of very different period and shape. Periodic orbits can thus help to characterize a chaotic system. [Cvitanovic, 1991; Kesaraju and Noah, 1994] We can use techniques that find periodic orbits in order to note changes in the system's parameters (hence, in its attractor).

4. FINDING PERIODIC ORBITS IN DATA

Periodic orbits in experimental data may be detected by several methods. Conventional spectrograms, as it happens, are not well suited to this task. Our signals are not generally sinusoidal. Spectrograms describe details of the remaining harmonic structure at the expense of long-range near-periodicity, an unfavorable trade-off here. Moreover, low power in a subharmonic will not be shown prominently in a spectrogram, yet just the existence of a subharmonic (even one with *no* power) is often highly significant dynamically.

One powerful but complicated alternative is to model the dynamical system locally, based on the collected data; the model may then be checked analytically for evidence of periodicity. [So *et al.*, 1996] However, modeling the dynamics depends on the system following a single attractor, precisely the condition we are trying to verify.

It is much easier to form histograms of "recurrence times": a count of the number of times that a signal value repeats (to within some tolerance) after some time interval, the *recurrence time*, as a function of that interval. [Lathrop and Kostelich, 1989] This gives us an "inventory" of the periodic orbits that sufficiently large fractions of the signal pass through (or near). For present purposes, however, it has a critical limitation: It cannot tell us *when* the collection of periodic orbits (hence, the attractor) changed. Furthermore, brief episodes of periodicity may be poorly represented in the histogram.

The "close-returns plot" [Mindlin and Gilmore, 1992] seems to provide almost what we need. The plot consists of dots at the time-versus-recurrence-time at which the signal values agree to within some chosen accuracy (typically a few percent in the work of Mindlin and Gilmore). That is, if the value at a time T agrees with that at $T+p$, then we plot a point at the coordinates $<T, p>$. If we see many points with the same value of p then we conclude that there is evidence of periodicity with period p: At many choices of time T, the system has found itself in a state to which it appears to return an interval p later. (The count of the number of close returns for each choice of p, summed over all T, is just the recurrence-time histogram.)

This is the basis of the technique explored here.

5. INTERPRETATION OF PERIODICITY DIAGRAMS

As the larynx opens and closes, the airflow rises and falls and the airflow (volume-velocity) signal passes repeatedly through a range of values. These pictures display, moment by moment, the interval (recurrence time) after which the same airflow level repeats: If the airflow levels at one instant and a certain interval later are nearly equal, the point corresponding to the instant (horizontal location) and interval (vertical location) is shown as bright; the closer the levels, the brighter the point; very dissimilar values are shown as dark. Thus, instead of an arbitrarily thresholded plot (the close-returns plot), we impose no threshold but display the closeness of the return as brightness. We refer to these images as "periodicity pictures" or "periodicity diagrams".

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permanently closed state of the larynx – on grounds of boredom.

[3] "Any attractor of a hyperbolic chaotic system is densely filled with periodic orbits"; that is, every state is arbitrarily close to a periodic orbit (in fact, an infinite number of them). Although most chaotic systems are probably not "hyperbolic" (a term which will not otherwise concern us here), they are nearly so – and the difference only causes the longest-period, most convoluted periodic orbits of the hyperbolic system to be missing from the actual one. The shorter and simpler periodic orbits are the most robust.

For a periodic system, all states repeat after some interval p and all multiples of p. Thus, for all times T, the corresponding picture will be bright at the recurrence time p, and at $2p$, $3p$, etc.: *Periodic motion produces horizontal lines across a picture, uniformly "stacked" in height.* This is shown most clearly on the "Loop" picture, Figure 1, generated from a sinusoid. The contrast with the "Noise" picture (Figure 2), generated from Gaussian white noise, is clear.

The same insight applies to some other features of the pictures: If the larynx passes through a similar range of states twice (or more) per period – that is, through one cycle of values, then through another that is similar but *not* identical, before both repeat – then the picture will show this as vertically alternating bright and less-bright horizontal lines. Such subharmonic ("period-doubling" or "octave-jump") behavior by the larynx is dynamically – and perhaps medically – significant.

Such a picture shows immediately when the larynx changes period, or even becomes aperiodic. If all periodicity stops, the region of horizontal lines has a triangular shape, with a boundary connecting the "top left" and "bottom right" of the region; this simply shows that earlier points (those to the left) have more repetitions (more lines vertically stacked) before the end. This is especially visible on the "Lorenz" pictures (Figures 2 and 3), derived from the well known Lorenz chaotic attractor.

This diagram also shows what a chaotic signal "looks like": temporary, scattered, nearly horizontal bright lines (often stacked) that show the presence of periodic orbits which the system nearly follows for short intervals. The structure of the attractor itself forces similar states to experience similar evolutions, regardless of the interval before the system returns to a similar state. Thus, the signal contains long-range order even though it cannot (if it is chaotic) have long-range predictability.

As it stands, this technique produces one strong artifact, even for a sinusoidal (scalar) signal. During any cycle, the signal reaches its maximum and minimum values only once per period. However, all intermediate values will occur at least twice per period, once when the signal is rising, once when falling. Consequently, we see an artifact, the steeply downward-sloping diagonal lines, that reflects this "false repetition" of the state. This artifact never forms uniformly stacked, horizontal line segments, the signature of periodicity, but it can obscure horizontal segments.

There is a solution, drawn from conventional analysis of NLD data: Instead of using a scalar signal, measuring the closeness of return of a single value, we can use a vector of values – ideally, the complete system state itself. Then, there cannot be false returns, because every close return of the vector must correspond to a close return of the state. Within broad limits, the expedient of using delayed copies of the signal itself serves just such a function. That is, we measure closeness not by a small difference between single values but by a simultaneously small difference between D consecutive values of the signal S: Symbolically, we compare

$$<S(T), S(T\text{-}1), \ldots, S(T\text{-}D+1)>$$

to

$$<S(T+p), S(T\text{-}1+p), \ldots, S(T\text{-}D+1+p)>,$$

instead of merely $S(T)$ to $S(T+p)$, before deciding how bright to show a point at $<T, p>$ in the periodicity diagram. This new processing accounts for the difference between the first (D=1) and second (D=5) "Lorenz" pictures.

Notice, incidentally, that there is *no need* to use the "correct" value of D: Too small a value will just produce occasional "false repetitions", unlikely to confuse a search for stacked, horizontal segments. This contrasts with many other NLD algorithms (notably, estimating the Lyapunov exponents), which can fail completely if D is even slightly too small.

6. RESULTS

All recordings are inverse-filtered to remove formants (oral-cavity resonances) and down-sampled to 2 kHz. In many of the recordings (of typical duration ~1 sec) that we have analyzed so far, the larynx vibrates with nearly constant period throughout the interval. Such recordings generate diagrams consisting largely of stacked, straight lines. Coming from a voice-pathology database, however, many do not. In the "jgc01" diagram, for example, we see evidence of period-doubling (700-1000 samples) and even period-tripling (1300-1600), with clear intervals when the larynx apparently follows a well-defined attractor. (In fact, the delay-space plots [not shown] of the corresponding sections are much "cleaner" than that of the whole.) In some cases, we apparently see chaos: a more-or-less uniform interval of short-term periodicity, reminiscent of some chaotic-attractor diagrams. The "josh1" diagram (near 700 samples, at 16 kHz), taken from a happy squawk by an infant, shows this pattern.

7. CONCLUSION

This method seems to give us a quick identification of single-mode dynamics, precisely what we need for other analytical techniques to succeed. Moreover, it should apply equally well to signals from any dynamical system that may be subject to occasional unpredictable attractor changes.

8. ACKNOWLEDGMENTS

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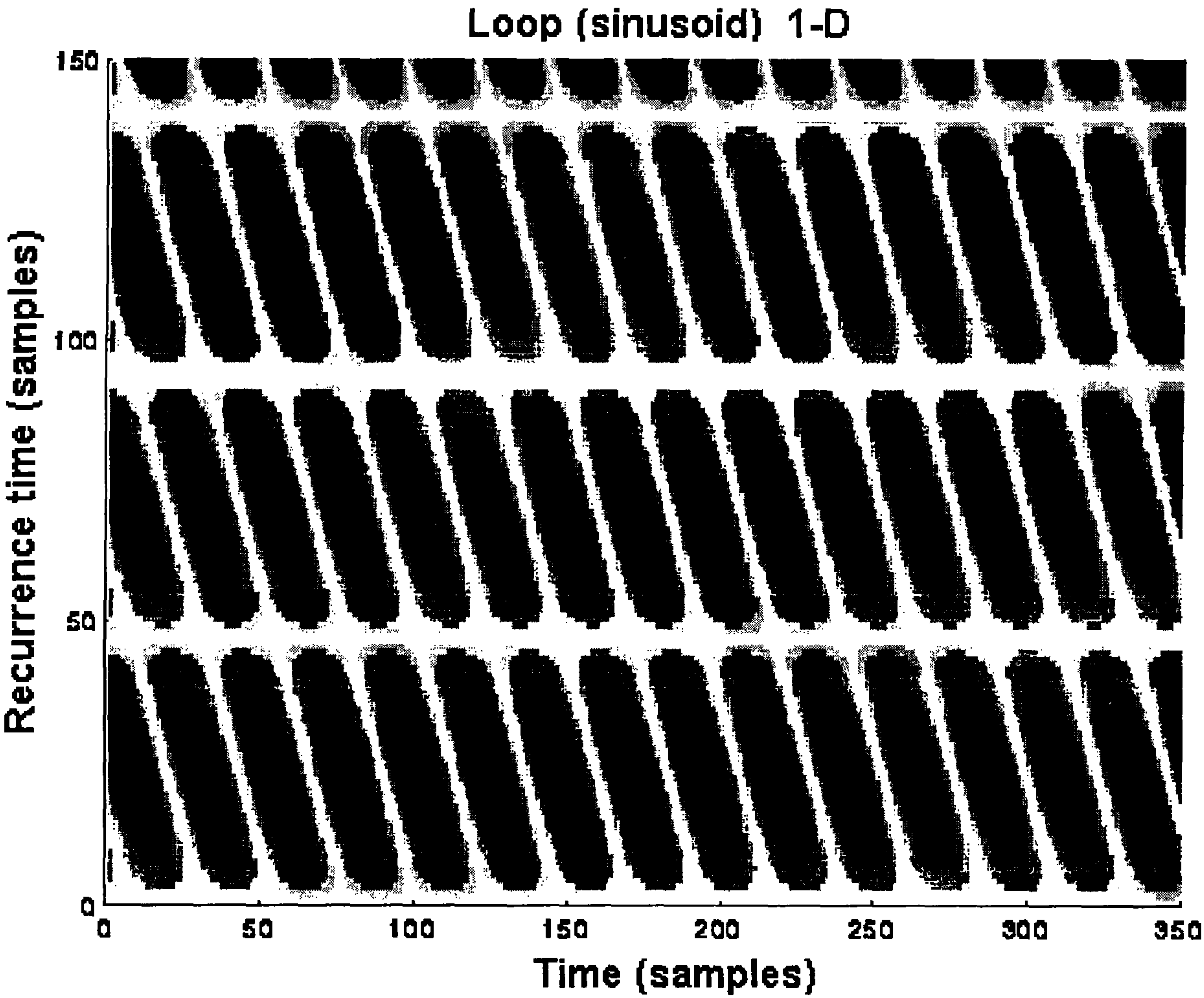

Loop (sinusoid) 1-D
Recurrence time (samples)
Time (samples)
0
50
100
150
200
250
300
350
0
50
100
150

Figure 1

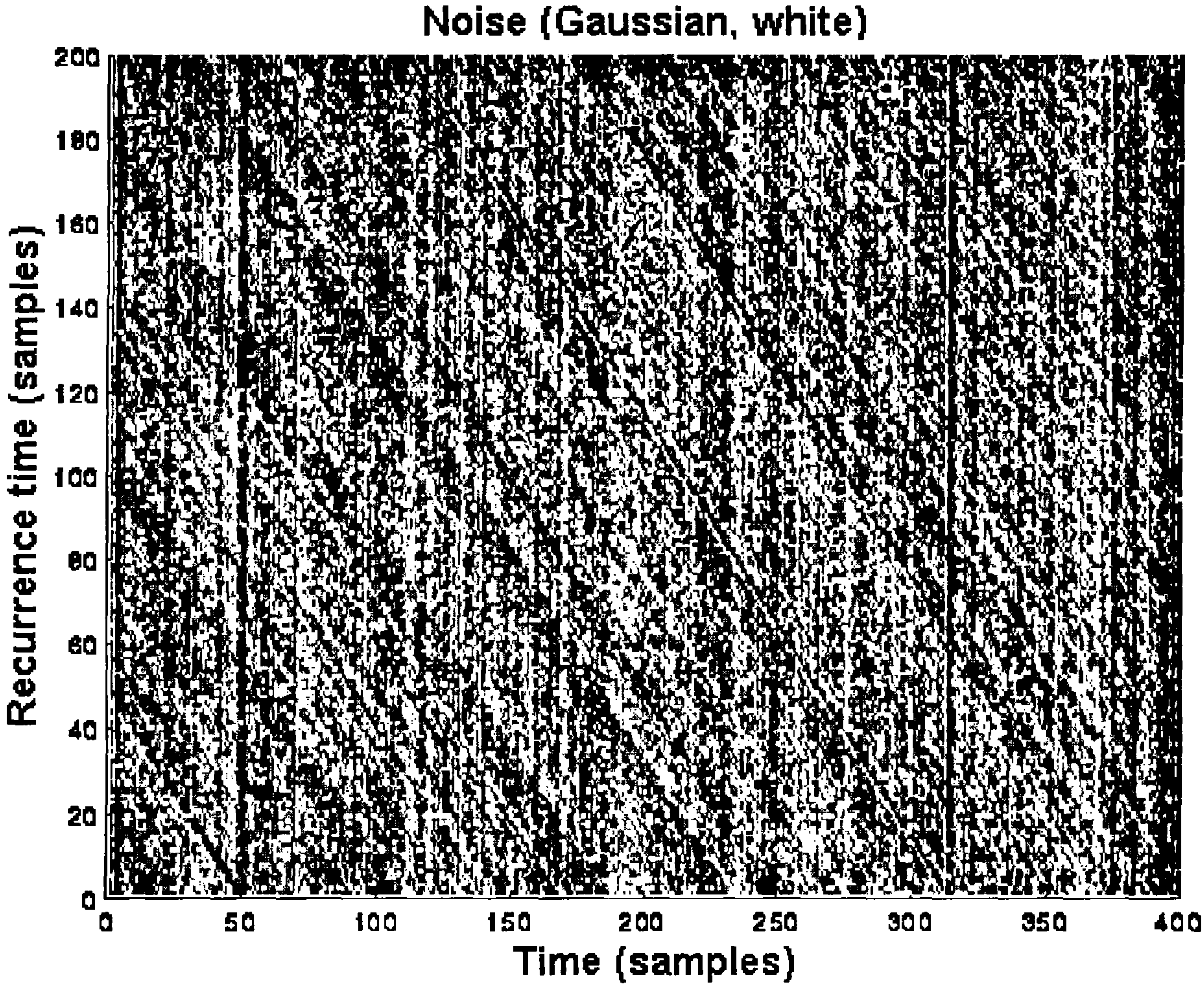
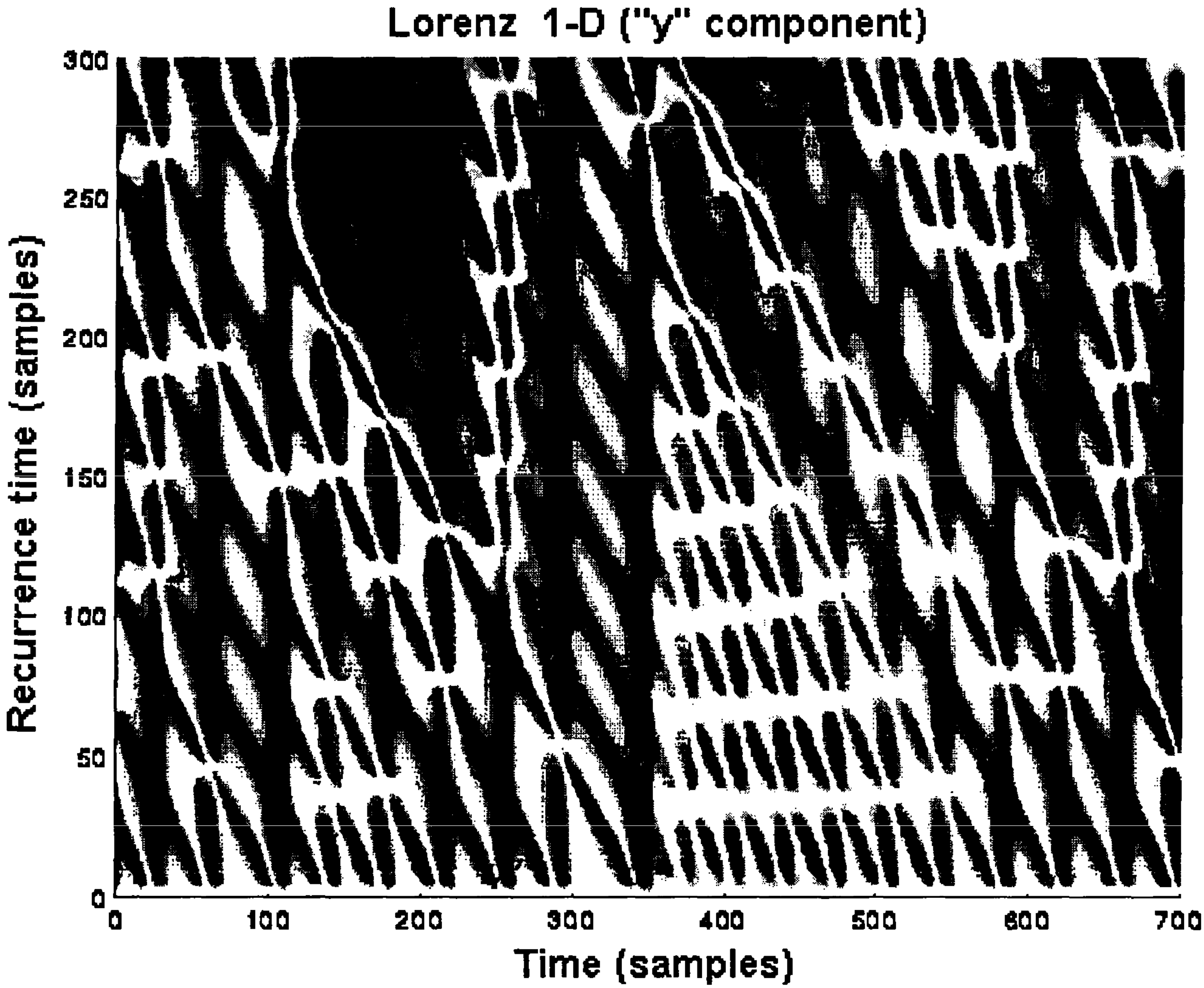
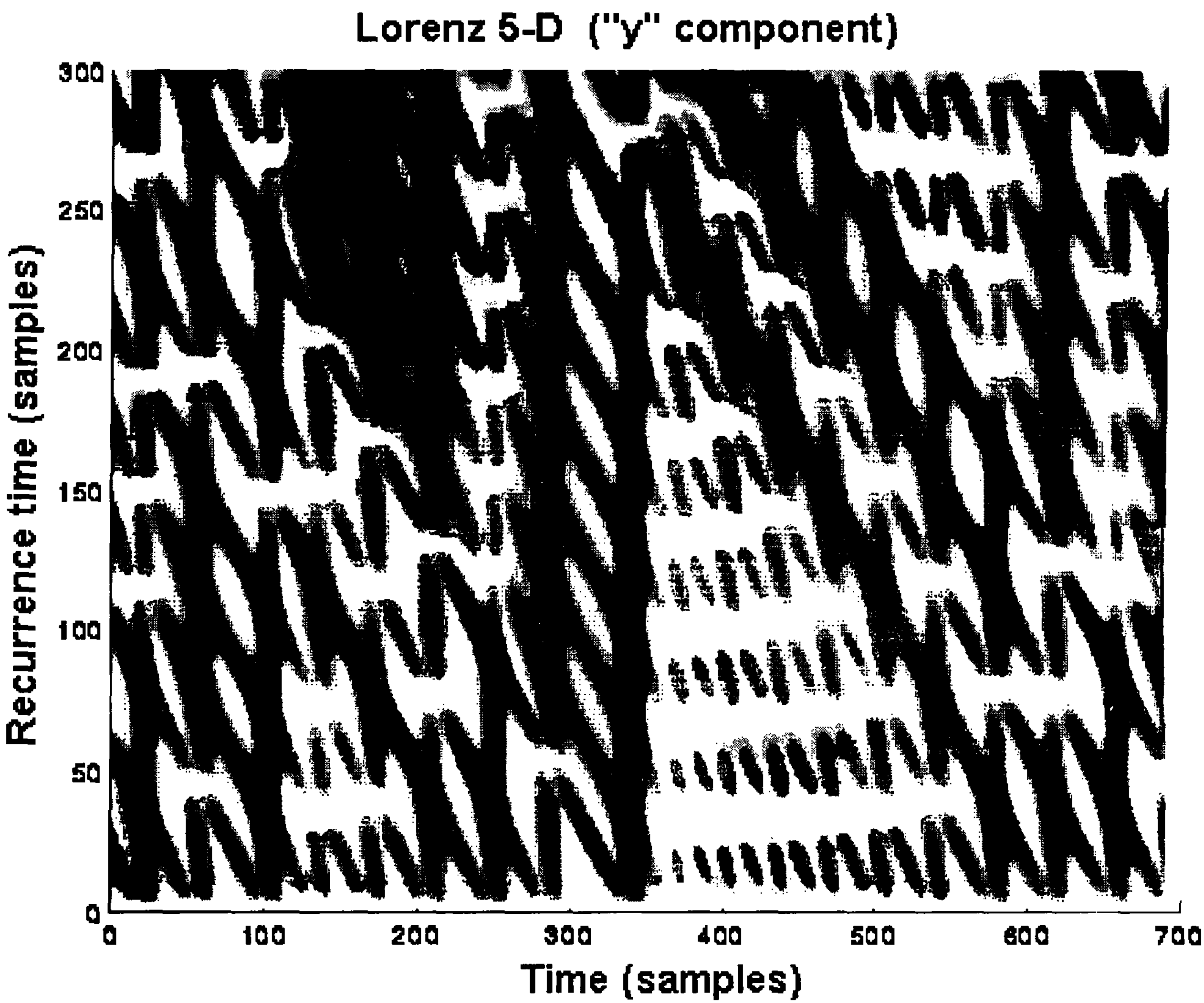

Noise (Gaussian, white)
Recurrence time (samples)
200
180
160
140
120
100
80
60
40
20
0
0
50
100
150
200
250
300
350
400
Time (samples)

Figure 2



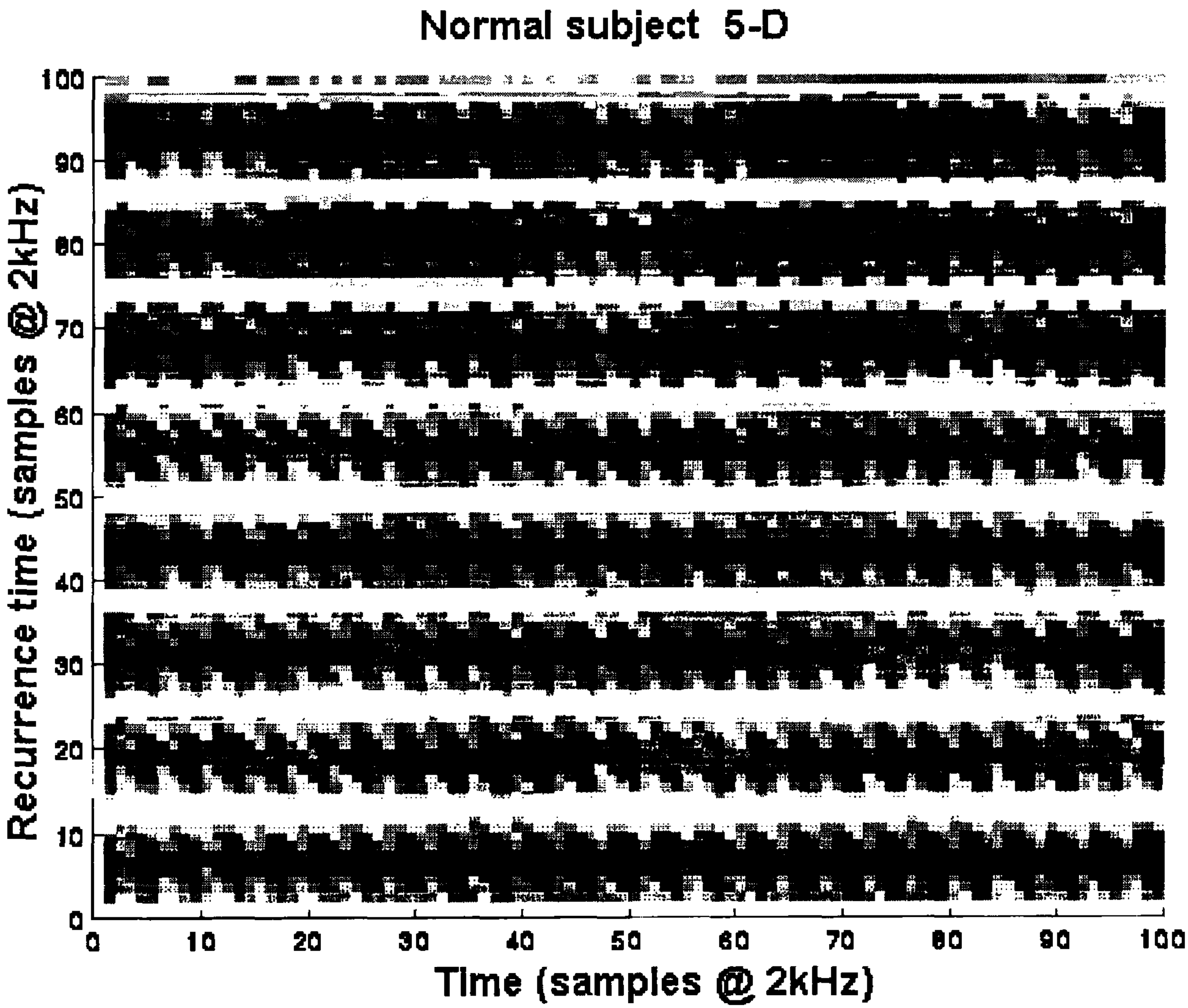
Lorenz 1-D ("y" component)
Recurrence time (samples)
Time (samples)
0
50
100
150
200
250
300
0
100
200
300
400
500
600
700

Figure 3



Lorenz 5-D ("y" component)
Recurrence time (samples)
0
50
100
150
200
250
300
Time (samples)
0
100
200
300
400
500
600
700

Figure 4



Normal subject 5-D
Recurrence time (samples @ 2kHz)
Time (samples @ 2kHz)
0
10
20
30
40
50
60
70
80
90
100

Figure 5

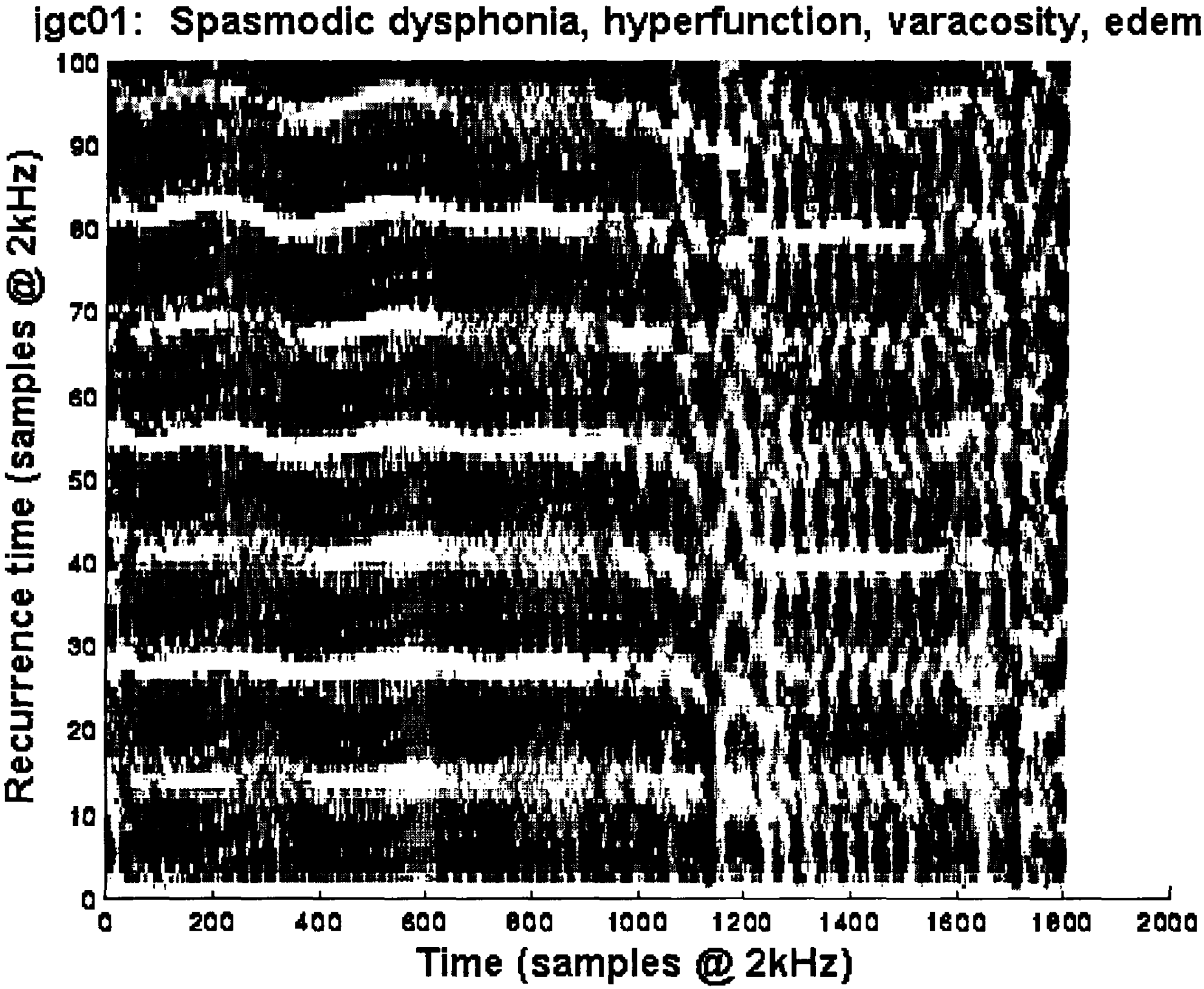

jgc01: Spasmodic dysphonia, hyperfunction, varacosity, edema
Recurrence time (samples @ 2kHz)
0
10
20
30
40
50
60
70
80
90
100
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Time (samples @ 2kHz)

Figure 6

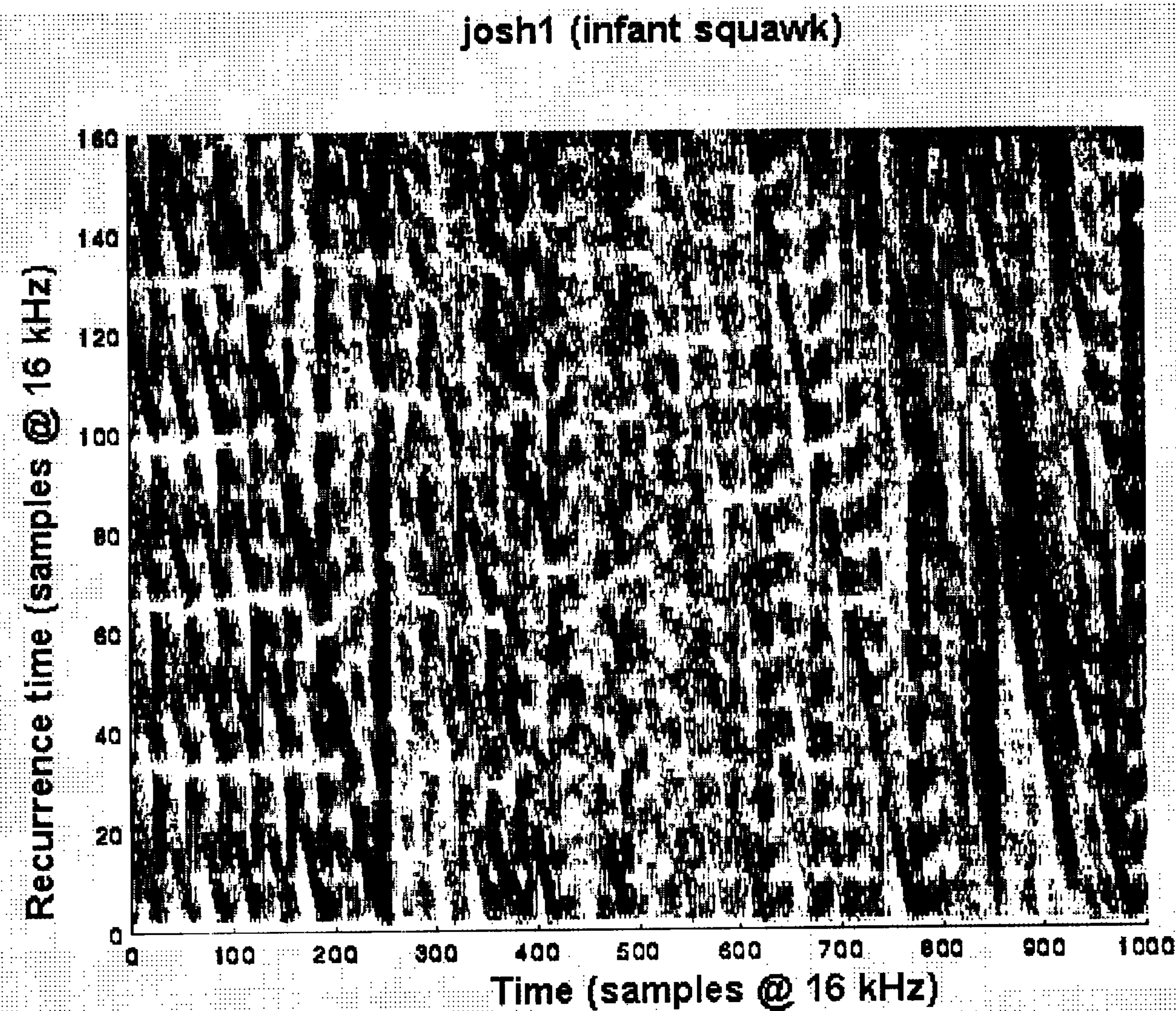

josh1 (infant squawk)
Recurrence time (samples @ 16 kHz)
0
20
40
60
80
100
120
140
160
0
100
200
300
400
500
600
700
800
900
1000
Time (samples @ 16 kHz)

Figure 7