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Nonlinear Approach to Characterization of Temporomandibular Joint Vibrations

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Abstract: A new approach is proposed to characterize and discriminate temporomandibular joint vibrations. It consists of three steps. First, signals recorded during each cycle of mandibular movement are unified into a single time series. Second, this time series is embedded in some multidimensional space. Third, nonlinear analysis methods are applied to extract the pertinent signal characteristics. In this way two groups of signals have been characterized; those in the first group were recorded from patients whose post-treatment results were bad and the ones in the second group were recorded from patients whose post-treatment results were good. But patients in both groups had

the same clinical features before treatment. It was shown that the two groups can be discriminated from each other by one parameter of the signals recorded from patients comprising the groups, the *coefficient of nonlinear forecasting*. It was also found that signals of the bad prognosis group share certain nonlinear characteristics although the patients comprising the group may have different pathologies.

Key Words: Temporomandibular joint vibration, nonlinear forecasting, Fourier methods, prognosis.

Introduction

Sounds detected with microphones and stethoscopes or vibrations detected with accelerometers over the temporomandibular joint (TMJ) during mandibular opening and closing have been attributed to subclinical or acute dysfunction of the joint (1). They are thought to be caused by various pathologies in the joint (2, 3, 4). However, recent literature on the subject abounds with reports describing the prevalence of TMJ sounds in non-patients also (5, 6, 7). Indeed, in one study (5) it was concluded that "TMJ sounds in non-patients are considered to be normal and not a manifestation of subclinical problems".

Most authors dealt with sounds recorded over the joint with a microphone or stethoscope rather than vibrations. The sounds were characterized as clicks, crepitations and popping sounds and were analyzed using Fourier methods or visual inspection (8-13) in nearly all but notably one study in which fractal analysis was used (14).

Materials and Methods

Experimental

In the present study we have recorded TMJ vibrations bilaterally for several cycles of mouth opening and closing by means of two accelerometers placed on the skin over the joints in patients with clinical symptoms. The degree of mouth opening was also monitored during each cycle. Both signals were simultaneously stored on the hard disk of a PC. Recordings were made twice from each patient, first when the patient presented to the Dental Clinic with complaints and then after a period of various types of treatment at our Physical Medicine and Rehabilitation Clinic. The details of signal recording, segmentation and feature extraction will be the subject of another paper. The present report is concerned with the analysis results obtained from two groups of patients, one comprising patients with bad prognosis and the other of patients with good prognosis.

Data Analysis

Unlike in methods employed by previous investigators, we have unified the TMJ signals of the

same patient recorded during different cycles of mouth opening and closing into a new single time series by appending them to one another. Thus a sufficient number of data points for the intended application was obtained. The reason for this procedure were the following:

1. Although the signal that is recorded during a single cycle of mouth opening and closing represents a time series, it contains too few data points for applying non-linear analysis methods. Therefore, nonlinear features can not be discerned from a single short record only. Appending different records to one another allows this.

2. In principle, each point in the time series represents some event in the dynamic process. According to the proposed approach, all points in this time series are informative since no “noisy” segments are included. On the other hand, the initial point of every TMJ signal segment is “influential” because it has no virtual “predecessor” from a previous segment and so this factor may distort some signal characteristics. But the coefficient of forecasting used here is not so sensitive to influential points due to averaging over all points. Also, a special procedure was used to eliminate the factor of influential points. Therefore, it can be said that all the data points considered reflect the same dynamic process and the estimates obtained from the analysis are quite reliable.

There are several different informative parameters which can be used for the purpose of signal characterization. In our case the question was which parameter would be the most appropriate. First, it was necessary to determine whether the constructed time series was linear or nonlinear. While spectral estimates would be most appropriate for a linear time series, parameters such as the information dimension or the Kolmogorov entropy would be most suitable for a nonlinear time series.

To determine the character of the time series, the information theoretic test [15 and references therein] was used. This test revealed that all the time series considered were nonlinear. Therefore, estimates of nonlinear dynamics were more appropriate than linear estimates.

There are also many parameters that describe features of nonlinear dynamics. What we have used here is the coefficient of nonlinear forecasting; the so-called translation error (16). This coefficient is used to recognize the deterministic dynamics of a time series (17). Recall that the dynamics of a signal can be deterministic (i.e. chaotic- generated by a strange attractor) or stochastic (random). In both cases, the

behaviour of the signal can be very complex and looks similar but a precise prediction of its behaviour can be obtained for the case of deterministic dynamics only.

In the present study the coefficient of nonlinear forecasting of the signal has been determined by a version of the nonlinear forecasting method after embedding the signal in a certain multidimensional space. This method and the results obtained from it are presented in the following section.

Nonlinear forecasting of TMJ signals

To study the dynamics of a signal, it is necessary to apply an appropriate numerical criterion. Recently a few criteria have been proposed for this purpose (16, 18-20). Here, we have applied the method described in Ref. 16. The reason for this choice is based on the following factors:

- A coefficient characterizing the dynamics makes a clear distinction between a chaotic behaviour and a stochastic one.
- The procedure to calculate this coefficient is sufficiently quick.

Denote by $s(1), s(2), \dots, s(N)$ the values of some one-dimensional time series. Using Taken’s embedding procedure (17, 18), we obtain the sequence of vectors:

$$x(j) = (s(j+L), \dots, s(j+(E-1)L)), \quad j = 1, \dots, N-(E-1)L \quad (1)$$

Here the embedding dimension and the lag time are designated by E and L respectively. The embedding parameters E and L are chosen by using the methods in Ref. 16 or by minimizing the translation error considered below.

Let x_1, x_2, \dots, x_k be the k nearest neighbours of some point x_0 . Next, designate by y_1, y_2, \dots, y_k the images of x_1, x_2, \dots, x_k after one time step (17). The translation vector $v_j = y_j - x_1$ and its average;

$$\bar{v} = \frac{1}{k+1} \sum_{j=0}^k v_j \quad (2)$$

are used to calculate the translation error

$$e_{tr} = \frac{1}{k+1} \sum_{j=0}^k \frac{\|v_j - \bar{v}\|^2}{\|\bar{v}\|^2}, \quad (3)$$

where the Euclidean length is designated by $\| \cdot \|$. It was shown that the translation error e_{tr} is greater than or

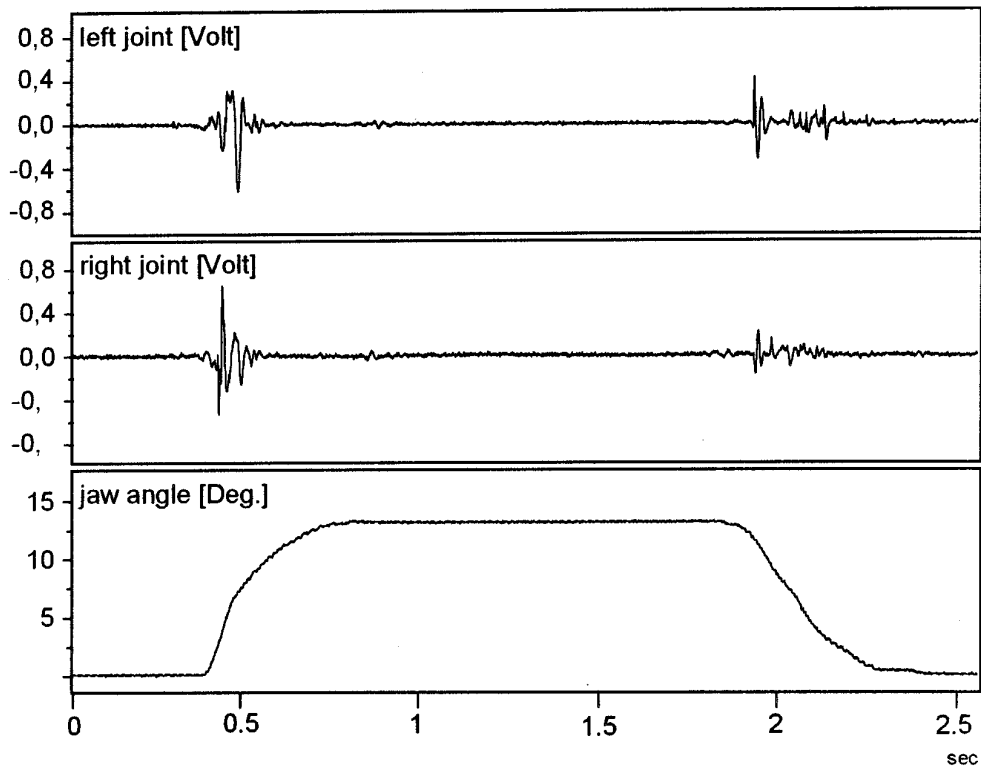


Figure 1. TMJ vibration signals recorded during one cycle of mandibular movement and goniometer (jaw angle) signal during the same cycle.

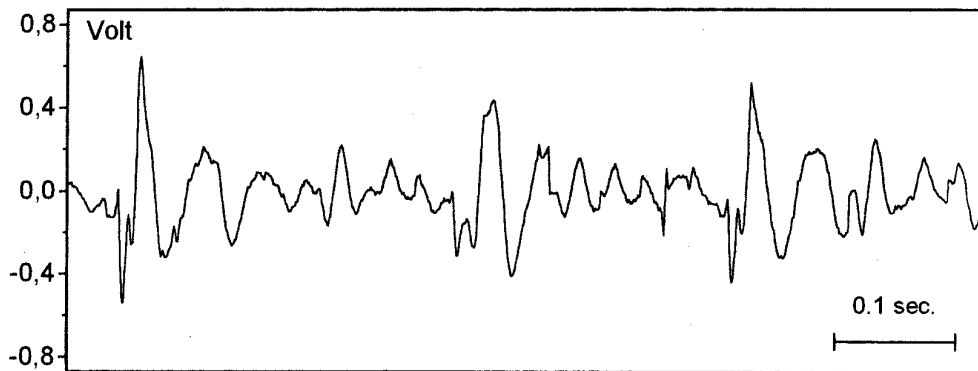


Figure 2. New time series obtained by appending signals of several cycles from one joint.

equal to unity for Gaussian noise (16). We have also verified this inference for a strongly non-Gaussian noise with the K-distribution probability density (21). At the same time, $e_{tr} \leq 0.1$ for the Henon attractor which is less than the value of e_{tr} for Gaussian noise. The translation

error was found to be in the same range for other attractors, including the logistic map and the Lorenz system (17). Thus, the translation error is a “good” discriminator of stochastic from deterministic time series. This inference is correct if the time series is not too short.

Table 1. Coefficient of Nonlinear Forecasting (Translation Error) Calculated From the New Time Series Signals of Patients with Bad and Good Prognosis.

Patients	Coefficient of Nonlinear Forecasting	Prognosis
1	5.090	Bad
2	4.751	Bad
3	8.563	Bad
4	2.896	Good
5	2.296	Good
6	3.172	Good
7	4.243	Good
8	3.872	Good
9	4.254	Good
10	4.649	Good

parameter for predicting treatment results. It should be noted that such a result can not be obtained with spectral approaches traditionally used. For example, amplitude spectra of the considered time series are given in Table 2. Amplitude spectra were obtained with FFT analysis using 128 data points with 80% overlap in each case. A rectangular window was used. As can be seen from this table the amplitude values and frequencies of maximum amplitude for different patients are quite "mixed" and do not allow any discrimination to be made between bad and good prognosis groups.

It is interesting to note that all the signals recorded from the second group of patients are of different types (clicks, popping and creptiations). However, it was possible to embed these signals in some multidimensional space where they had similar values of the coefficient of nonlinear forecasting and which could be discriminated from those of patients in the first group.

patient no and prognosis	no of FFT blocks	maximum amplitude (volt)	frequency of maximum amplitude (Hz)	mean maximum amplitude±S.D. (volt)	mean maximum frequency±S.D. (Hz)
1B	5	0.136	93.75	0.117±0.012	100.00±12.50
2B	29	0.463	15.63	0.283±0.105	34.48±11.15
3B	52	0.939	78.13	0.471±0.318	86.24±28.66
1G	63	0.529	46.88	0.302±0.088	42.99±17.82
2G	10	0.305	46.88	0.251±0.030	35.94±07.16
3G	30	0.351	78.13	0.227±0.065	67.71±17.74
4G	26	0.226	46.88	0.108±0.057	72.72±31.53
5G	33	0.137	93.75	0.084±0.032	57.29±24.23
6G	38	0.433	62.50	0.197±0.099	67.85±15.33
7G	29	0.145	31.25	0.084±0.025	42.03±13.67

Table 2. Amplitude Spectra of Time Series Signals Obtained from Patients with Good and Bad Prognosis.

B: Bad prognosis; G: Good prognosis

Results

Figure 1 shows a typical TMJ vibration signal and the goniometer (angle) signal recorded during one cycle of mouth opening and closing. Figure 2 is the plot of the new time series obtained by appending to one another the TMJ signals of several cycles of mandibular movement as explained previously. The coefficient of forecasting (translation error) was calculated from the time series obtained in this fashion.

The values of the translation error obtained at the embedding dimension 2 and lag time 6 are presented in Table 1. It is clearly seen that all values obtained from the signals of patients in the first group (i.e. the three patients with bad prognosis) are larger than those of the patients in the second group (i.e. the seven patients treated successfully). Thus, we find that the coefficient of nonlinear forecasting -the translation error- is a useful

Discussion

There are mainly two findings of this study. First, a new approach for processing TMJ signals is introduced. This approach is based on estimates of nonlinear dynamics. Its efficacy has been demonstrated for a case in which conventional estimates have failed. Second, it has been shown that TMJ signals arising from probably different pathologies which are difficult to treat can have common nonlinear characteristics (the embedding dimension, lag time and the range of the coefficient of nonlinear forecasting) allowing to distinguish them from the signals of patients who respond better to treatment (i.e. good prognosis).

Thus, these results imply that wider applications of nonlinear methods to TMJ signals are needed in search for their common features and how they may be used to predict the results of treatment in clinical practice.

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