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Detection of chaos in human fatigue mechanomyogarphy signals

Hong-Bo Xie., Yong-Ping Zheng, *Senior Member, IEEE*., and Jing-Yi, Guo

***Abstract*—We undertake the study of the chaotic nature of mechanomygraphy (MMG) signal by recourse to the recent developments in the field of nonlinear dynamics. The MMG signals were measured from biceps brachii muscle of 5 subjects during fatigue of isometric contraction at 80% maximal voluntary contraction (MVC) level. Deterministic chaotic character was detected in all data by using the Volterra-Wiener-Korenberg model and noise titration approach. The noise limit (NL), which is a power indicator of chaos of fatigue MMG signals, is 22.2000 ± 8.7293. Furthermore, we studied the nonlinear dynamic features of MMG signals by computing their correlation dimension D_2 , which is 3.3524 ± 0.3645 across all the subjects. These results indicate that MMG is a high-dimensional chaotic signal and support the use of the theory of nonlinear dynamics for the analysis and modeling the MMG signals.**

I. Introduction

THE EMG signal is the electrical manifestation of the neuromuscular activation associated with muscle contraction [1], while the mechanomyography (MMG) signal records and quantifies the low-frequency lateral oscillations of active skeletal muscle, which reflects the "mechanical counterpart" of the motor unit electrical activity as measured by electromyography (EMG) [2]. It has been recently recognized that EMG signal exhibits high-dimensional deterministic chaos [3, 4], Therefore, methods of nonlinear dynamics (NLD) analysis have been introduced to EMG to get a better insight into the complex signal.

Though the great success has been achieved on nonlinear analysis of EMG, the present methods used in MMG analysis are most commonly based on the assumption that the signal is linear stochastic processes, and the temporal and frequency spectrum characteristics were used. For example, the root mean square (RMS), the mean frequency, the second-order central moment (i.e., the variance of the power spectral density), and the normalized third central moment (i.e., the skewness) of MMG signal have been estimated to quantify the local muscle fatigue [5-7]. Outtenl et al. applied the burg algorithm and three different criteria to extract the MMG auto-regressive model coefficients and to characterize the MMG-force relationship at different force level [8]. Recently, wavelets have also been suggested for analyzing MMG signals [9]. Although these techniques do characterize MMG signals, perhaps, nonlinear techniques may be needed to ascertain the characteristics of these physiological signals, and to fully characterize their pattern. To our best knowledge, few researchers have so far examined the nonlinear nature of MMG, though it is known that MMG presents high complexity as EMG.

Volterra–Wiener–Korenberg (VWK) series approach has been developed by Barahona and Poon to detect nonlinearity in a time series [10]. Later, numerical titration technique, an extension of the VWK algorithm, was given by the group to detect and quantify chaos intensity in a chaotic system even if the time series is short and noisy in nature [11]. The Gaussian kernel algorithm to determine the fractal dimension was proposed by Diks and offers several advantaged over earlier methods (e.g., Grassberger-Procaccia) [12]. The method is technically more complex but is in practice more reliable, more robust under the noisy data, and less prone to misinterpretation.

So far, little attention has been paid on the utilization of nonlinear dynamics tools to analyze the MMG signals. In this paper, some recent developments in the field of NLD (e.g., the VWK model [10]; GKA method [12]; the numerical titration method [11]) are employed with the aim of detecting and locating determinism and nonlinearity in the system governing the time behaviour of MMG signals.

II. Methodology

A. *MMG data sets*

The MMG signals analyzed in this paper were recorded during the voluntary isometric contractions of five healthy human subjects. The accelerometer (EGAS-FS-10-VO5, Entran Inc, Fairfield, NJ) was fixed on the biceps brachii using double adhesive tape. When the experiment began, the subject was asked to perform an elbow flexion against the lever arm to the 80% of his/her maximal voluntary contraction and maintained this value through the visual feedback of the torque showed on the screen. The test was stopped when the torque dropped to approximately 70% of the MVC, which indicates the muscle exhausted. The gain of the MMG signal was 5000 with a 5–250 Hz bandwidth. Signals from the sensor

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H. B. Xie was with Jiangsu University, Jiangsu, 212013 PR of China. He is now with the Department of Health Technology and Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong SAR, P.R.China (e-mail: xiehb@sjtu.org).

Y. P. Zheng (corresponding author) is with the Department of Health Technology and Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong SAR, P.R.China (Tel: 852-27667664; fax: 852-23624365; e-mail: ypzheng@ieee.org).

J. Y. Guo is with the Department of Health Technology and Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong SAR, P.R.China (e-mail: 05901780r@inet.polyu.edu.hk).

were acquired at 500 Hz and stored

in computer. The stationary segment in the fatigue state with 1000 points was selected for further nonlinear analysis.

B. Test for Nonlinearity

The proposed framework for MMG analysis in present work consisted of three logical steps. Science nonlinearity is a necessary condition for chaoticity, the present step was to detect nonlinearity using the VWK model method. The second step was to detect chaoticity based on the numerical titration procedure. At last, the GKA algorithm was applied to determine the correlation dimension for characterizing the complex temporal behavior of the chaotic trajectory from measured MMG time series data.

VWK test method is a kind of nonlinear detection of time series based on linear and nonlinear Volterra-Wiener-Korenberg model. Technically, it first produces the linear and nonlinear predicted data from the original time series and compares their information criteria to detect the nonlinearity of the original data. It is capable of robust and highly sensitive to statistical detection of deterministic dynamics, including chaotic dynamics, in experimental data set. Assuming that a time series is univariate, a discrete VWK series can be calculated as follows [10]

$$\begin{aligned} x_n^{cal} &= a_0 + a_1 x_{n-1} + a_2 x_{n-2} + \cdots a_k x_{n-k} + a_{k+1} x_{n-1}^2 \\ &\quad + a_{k+2} x_{n-1} x_{n-2} + \cdots + a_{M-1} x_{n-k}^d \\ &= \sum_{m=0}^{M} a_m z_m(n) \end{aligned} \tag{1}$$

where the memory k and combination degree d correspond to the embedding dimension and the degree of nonlinearity of the model, respectively. The coefficients a_m are recursively estimated through a Gram-Schmidt procedure from linear and nonlinear autocorrelations of the data itself.

There is the following information criterion in accordance with the parsimony principle:

$$C(r) = \log \varepsilon(r) + r/N \tag{2}$$

$$\varepsilon(k,d)^2 = \frac{\sum_{n=1}^{N} (x_a^{cal}(k,d) - x_n)^2}{\sum_{n=1}^{N} (x_n - \overline{x})^2} \tag{3}$$

$$\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_n \tag{4}$$

where $r \in [1, M]$ is the number of polynomial terms of the truncated Volterra expansions from the given pair $\{k, d\}$, $\varepsilon(k,d)^2$ is a normalized variance of the error residuals.

For each series, the best linear model is determined by searching for the k^{lin} which minimizes $C(r)$ with $d = 1$. The procedure is repeated with increasing k and $d > 1$, to achieve the best nonlinear mode. This leads to two competing models with the corresponding error standard deviations ε_{orig}^{lin} and ε_{orig}^{nl}. It indicates that the original series is nonlinear if $d_{opt} > 1$. Otherwise, it may be inferred that the original series is not chaotic or the chaotic component is too weak to be detected. A parametric *F*-test is applied to

reject the hypothesis that nonlinear modes are not better than linear models as one-step-ahead predictors if $\varepsilon_{oig}^{lin} > \varepsilon_{orig}^{nl}$ in the statistical sense.

C. Titration Test for Chaos

If the null hypothesis is rejected in the above step, namely if a nonlinear model best describes the data, the noise titration process is applied to detect the chaos in a nonlinear time series. White noise of increasing standard deviation (δ) is added to the time series until its nonlinearity goes undetected (with a prescribed level of statistical confidence) by the above process. The corresponding amount of noise is called "noise limit" (NL). A NL above zero indicates the presence of chaos and provides an estimate of its intensity within the experimental time series [11]. Conversely if NL=0 nonlinearity is not detected. This can mean that the time series is not chaotic or that the chaotic component of the signal is already neutralized by the background noise in the data [11]. The condition NL>0 therefore provides a simple sufficient case for chaos.

D. Estimation for Correlation Dimension

The Gaussian kernel algorithm to determine the correlation dimension is a generalized form of GP algorithm and offers several advantages over GP method. It is specifically useful for the noisy time series and works well for different noise sources. In a representative trial, the Lorenz system was added by different types of independent and identically distributed (IID) noise, i.e., Gaussian, uniform, and a combination of the Gaussian with uniform noise. The method could accurately capture the underlying correlation dimension of the system even for pure Gaussian IID noise up to 50% (noise level), pure uniform IID noise to 20%, and combined noise to 40% [12]. Therefore, the present work relies on the GKA method.

III. Results

An illustration of a typical raw MMG signal of subject 2 is shown in Fig.1 and its phase space reconstruction was obtained as shown in Fig. 2

The VWK model method has been applied to the MMG sequences to test the nonlinearity. In all the subjects, $C(r)$ vs. number of terms r have been analyzed for both linear and nonlinear models for varying parameters k and d.

In all the cases, the null hypothesis of linearity was rejected using *F*-test. The finding indicated that the analyzed MMG signals were all nonlinear. $C(r)$ vs. r plots for the MMG signal shown in Fig. 1 has been depicted in Fig. 3. The plots for other subjects were similar, i.e., $C_{orig}^{lin}(r)$ is significantly higher than $C_{orig}^{nl}(r)$. The results showed that, for MMG signals, the nonlinear model would be more predictive than the linear model.

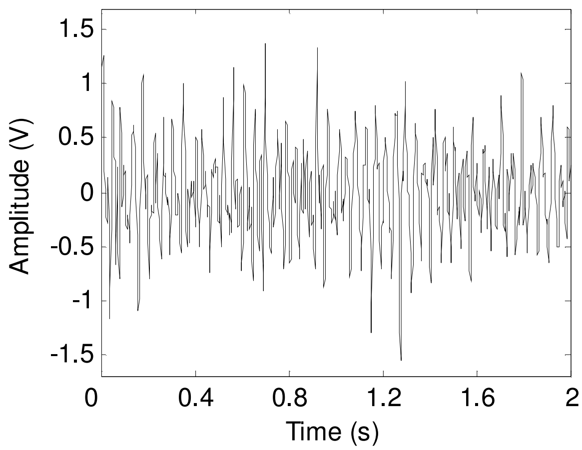

Fig. 1. Typical raw MMG signal recorded at Biceps from subject 2.

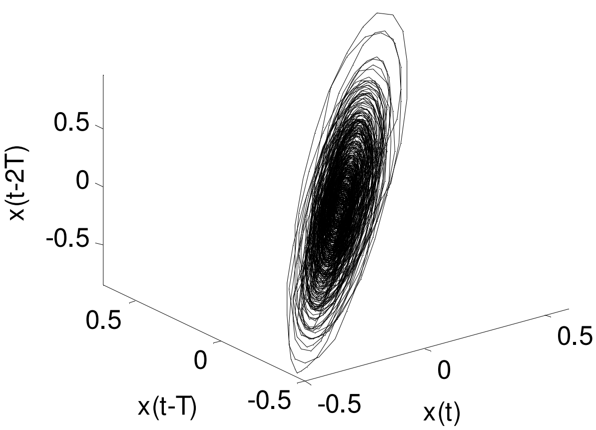

Fig. 2. Attractor of MMG signal, obtained by phase reconstruction of typical raw MMG signal.

Nonlinearity has been detected in MMG signals of all subjects. Next, according to the chaotic titration method, we add the white noise to MMG signal till the VWK nonlinear identification method could not detect the nonlinear dynamics. Titration on each of the MMG signal has been performed with an increment of 1% noise at every step. Fig. 4 show $C(r)$ vs. r plots for the MMG signal shown in Fig. 1 for 9%, 18%, and 27% noise additions, respectively. The highest of these noise limit values obtained in each subject are listed in Table. 1. Clearly, the noise limit yielded by the noise titration procedure for each data set was above zero which depicted a sufficient condition for chaos in the fatigue MMG signals. As mentioned in Section 2, since GKA method overcomes many of the intractable problems posed by GP algorithms, it is used to determine the correlation dimension of the MMG signals.

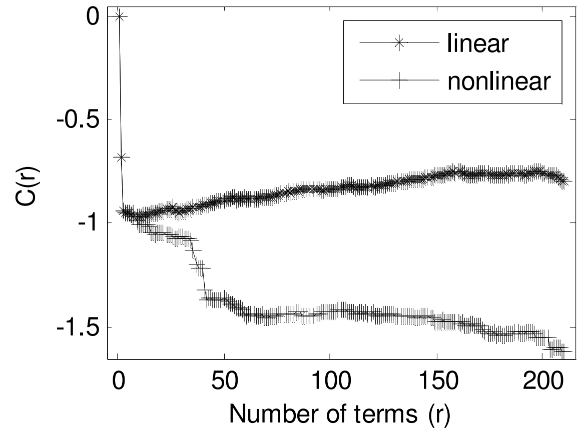

Fig. 3. Linear and nonlinear model fits using the Volterra-Wiener-Korenberg series for the MMG signal.

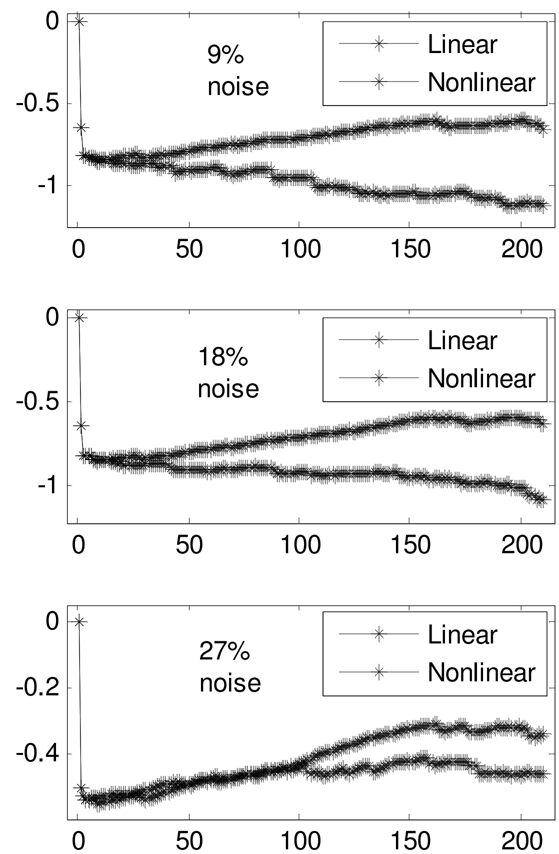

Fig. 4. $C(r)$ vs. r plots for the MMG signal when added noise is (a) 9%, (b) 18%, and (c) 27% (noise limit).

Fig. 7 shows the plot of correlation dimension vs. varying embedding dimension based on the segment of the MMG data taken form the subject 2. With increasing the embedding dimension m, the correlation dimension D_2 first embedding dimension m, the correlation dimension D_2 first rises and saturates at embedding dimension of 7, and thereafter slightly fluctuated. The average value and corresponding standard deviation were obtained over $m = 7-20$, giving $D_2 = 3.8428 \pm 0.2310$. The results of the correlation dimension estimation of the other subjects were similar, and the mean and standard deviation

of D_2 across 5 subjects were 3.3524 and 0.3645, respectively. This measurement indicated the mechanical activity of the muscle within this segment of MMG can be described by $3-4$ active degrees of freedom. Hence, the dynamical behavior of the muscle's mechanical activity is mostly likely to originate from the high-dimensional chaos.

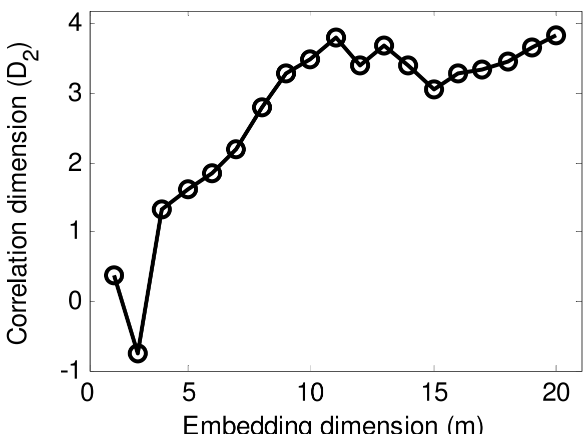

Fig. 5. The measurement of correlation dimension D_2 as a function of embedding dimension m

TABLE I
THE NOISE LIMIT VALUES FOUND BY USING THE NOISE TITRATION PROCEDURE IN THE 5 SUBJECTS.

subjects	Noise level (%)	*k*	d
1	16	6	4
2	27	6	4
3	12	6	4
4	34	6	4,5
5	22	6	5
Mean	22.2000		
S.D.	8.7293		

IV. CONCLUSIONS

In the course of muscle contraction, there is strong electromechanical coupling in the motor system. The EMG signal reflects the generation, propagation and extinction of motor unit action potentials. In the meantime, the electrical impulses (spikes) of the motor system are converted to mechanical "ripples" (twitch contractions) of the related motor unit, which are connected to innervating motor neurons via neuromuscular junctions. This mechanism leads to motor unit recruitment, firing pattern, and/or synchronization are reflected in both the EMG and the MMG signals [2]. Previous studies of Nieminen and Takala [3] have noted the EMG signals were a chaotic signal based on the modeling study of biceps brachii during isometric contraction. However, little attention has been given to the nonlinear structure of another outcome of muscle contraction. In the present study, the positive value of noise limit, as shown in Table. 1 and the correlation dimension from 2.9476 to 3.8428 were indicators that MMG signals in fatigue state of all observed subjects were a chaotic signal, and were generated by nonlinear dynamics systems. Our results advocate the use of the theory of nonlinear dynamics for the analysis and modeling of the MMG.

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