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Quantitative performance analysis of four methods of evaluating signal nonlinearity: Application to uterine EMG signals.

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***Abstract*—Recently, much attention has been paid to the use of nonlinear analysis techniques for the characterization of biological signals. Several measures have been proposed to detect nonlinear characteristics in time series. The sensitivity of several nonlinear methods to the actual nonlinearity level and their sensitivity to noise have never been evaluated. In this paper we perform this analysis for four methods that are widely used in nonlinearity detection: Time reversibility, Sample Entropy, Lyapunov Exponents and Delay Vector Variance. The evolution of methods with complexity degree (*CD*) and with different Signal to Noise Ratio was computed for the four methods on nonlinear synthetic signals. The methods were then applied to real uterine EMG signals with the aim of using them to distinguish between pregnancy and labor signals. The results show a clear superiority of the Time reversibility method, in classification of pregnancy and labor signals.**

I. INTRODUCTION

One of the most common ways of obtaining information about neurophysiologic systems is to study the features of the signal(s) by using time series analysis techniques. They traditionally rely on linear methods in both time and frequency domains [1]. Unfortunately, these methods cannot give any information about nonlinear features of the signal. Due to the intrinsic nonlinearity of most biological systems, these nonlinear features may be present in physiological data. Recently, much attention has been paid to the use of nonlinear analysis techniques for the characterization of biological signal [2]. Indeed, this analysis gives information about nonlinear features of these signals, raised from the underlying nonlinear processes of physiological mechanisms of most biological systems. The uterus is a very poorly understood organ. It is deceptively simple in structure but its behavior, as observed by EMG, when it moves from pregnancy towards labor, indicates that there are numbers of interconnected control systems involved in its functioning (electric, chemical, mechanical). When working together, they give rise to the nonlinear character observed in the EHG. There is a growing literature reporting non linear biosignal analysis such as EEG [3], ECG [4], HRV [5], EMG [6] and EHG [7].

Several applications of nonlinear analysis methods have been done on the uterine EMG signals. We can cite here the comparison between Approximate Entropy, Correntropy and Time reversibility [7], the use of Sample Entropy [8] and the use of Detrended Fluctuation Analysis [4]. In most of these studies the authors have reported some practical disadvantages of the methods like the huge calculation time due to the use of surrogates analysis, or promising but inconclusive results due to the small database available. Sensitivity analyses and robustness study of non-linearity measures, which is the main objective of this paper, are rare in the literature.

Four methods: Time reversibility [9], Sample Entropy [8], Lyapunov Exponents [10] and Delay Vector Variance [11] were used in the this work. Sensitivity analysis of these methods to the complexity degree (*CD*) of signal and robustness analysis were made on synthetic signals where the *CD* is controlled. Finally, the methods were applied to real EHG signals for use in differentiation between pregnancy and labor contractions. This paper presents the comparison of methods and concludes that Time reversibility method is the best of the four methods in classifying pregnancy and labor EHG.

II. MATERIAL AND METHODS

A. Data

1. Synthetic signals

To study the evolution of methods, we used the Henon synthetic model to generate nonlinear stationary signals where *CD* is controlled.

The Henon map is a well-known two-dimensional discrete-time system given by

$$Y_{t+1} = c - Y_t^2 + CD * X_t\ ,$$
$$X_{t+1} = Y_t\ ,$$

Where Y_t , X_t represent dynamical variables, *CD* is the complexity degree and *c* is the dissipation parameter. In this paper we use *c*=1 [12] and *CD* ϵ [0, 1] to change the model complexity [13]. The number of points is fixed at 1000.

In the robustness analysis, we add to the synthetic signal white Gaussian noise with the same duration, once with a fixed 5db SNR, with CD varying between 0 and 1, then with variable levels 1db, 2db, 5db, 10db, 100db, with CD fixed to 0.8.

2. Real signals

The methods used here are “monovariate” in that we used only one bipolar channel from the 4*4 recording matrix located on the women's abdomen. This channel is located on the median vertical axis of the uterus (see [14] for details). The signal was recorded on women in France and in Iceland.

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In Iceland we recorded signals on 22 women: 11 recorded during pregnancy (33-39 week of gestation) and 11 during labor (39-42 week of gestation). The measurements were performed at the Landspitali University hospital, following a protocol approved by the relevant ethical committee (VSN 02-0006-V2). The sampling frequency was 200 Hz.

In France we recorded signals on 27 women: 25 recorded during pregnancy (33-39 week of gestation) and 2 during labor (39-42 week of gestation). The measurements were performed at the Center of Amiens for Obstetrics and Gynecology, following a protocol approved by the local ethical committee. The sampling frequency was 256 Hz.

The EHG signals were segmented manually to extract segments containing uterine activity bursts. After segmentation we got 115 labor bursts and 174 pregnancy bursts. The analysis below was applied to these segmented uterine bursts.

B. Methods

1. Time reversibility

A time series is said to be reversible only if its probabilistic properties are invariant with respect to time reversal. Time irreversibility can be taken as a strong signature of nonlinearity [7]. In this paper we used the simplest way, described in [9] to compute time reversibility for signal:

$$Tr(\tau) = \left(\frac{1}{N-\tau}\right) \sum_{n=\tau+1}^{N} (S_n - S_{n-\tau})^3$$

where N is the signal length and τ is the time delay.

2. Sample Entropy

Sample Entropy (SampEn) is the negative natural logarithm of the conditional probability that a dataset of length N, having repeated itself for m samples within a tolerance r, will also repeat itself for $m+1$ samples. Thus, a lower value of SampEn indicates more regularity in the time series. We used the way, described in [8] to compute SampEn:

For a time series of N points, $x_1, x_2, \ldots, x_N$, we define subsequences, also called template vectors, of length m, given by: $y_i(m) = (x_i, x_{i+1}, \ldots, x_{i+m-1})$ where $i = 1, 2, \ldots, N-m+1$. Then the following quantity is defined: $B_i^m(r)$ as $(N-m-1)^{-1}$ times the number of vectors X_j^m within r of X_i^m, where j ranges from 1 to N-m, and $j \neq i$ to exclude self-matches, and then define:

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r)$$

Similarly, define $A_i^m(r)$ as $(N-m-1)^{-1}$ times the number of vectors X_j^{m+1} within r of X_i^{m+1}, where j ranges from 1 to N-m, where $j \neq i$, and set

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r)$$

The parameter SampEn(m,r) is then defined as $lim_{N\to\infty}\{-\,ln[A^m(r)/B^m(r)]\}$, which can be estimated by the statistic:

$$SampEn(m, r, N) = -\ln[A^m(r)/B^m(r)]$$

N is the length of the time series, m is the length of sequences to be compared, and r is the tolerance for accepting matches.

3. Lyapunov Exponents

Lyapunov exponent (LE) is a quantitative indicator of system dynamics, which characterizes the average convergence or divergence rate between adjacent tracks in phase space. We used the way, described in [10] to compute LE:

$$\lambda = \lim_{t \to \infty} \lim_{\|\Delta_{y_0}\| \to 0} \left(\frac{1}{t}\right) log(\| \Delta_{y_t} \| / \| \Delta_{y_0} \|),$$

Where $\| \Delta_{y_0} \|$ and $\| \Delta_{y_t} \|$ represent the Euclidean distance between two states of the system respectively to an arbitrary time t_0 and a later time t.

4. Delay Vector Variance

The delay vector variance (DVV) method is used for detecting the presence of determinism and nonlinearity in a time series and is based upon the examination of local predictability of a signal. We use the measure of unpredictability σ^{*2} described in [11]:

A time series can be represented conveniently in phase space by using time delay embedding. When time delay is embedded into a time series, it can be represented by a set of delay vectors (DVs) of a given dimension. If m is the dimension of the delay vectors then it can be expressed as $X(k) = [x_{(k-m\tau)} \ldots x_{(k-\tau)}]$, where τ is the time lag. Now for every DV $X(k)$, there is a corresponding target, namely the next sample x_k. A set $\beta_k(m, d)$ is generated by grouping those DVs that are within a certain Euclidean distance (d) to DV $X(k)$. This Euclidean distance will be varied in a manner standardized with respect to the distribution of pair wise distances between DVs. Now for a given embedding dimension m, a measure of unpredictability σ^{*2} (target variance) is computed overall sets of β_k.

The mean μ_d and the standard deviation σ_d are computed over all pair wise Euclidean distances between DVs given by $\|x(i) - x(j)\|$ $(i \neq j)$. The sets $\beta_k(m, d)$ are generated such that $\beta_k = \{x(i) \backslash \|x(k) - x(j)\| \leq d\}$ i.e., sets which consist of all DVs that lie closer to $X(k)$ than a certain distance d, taken from the interval $[\mu_d - n_d * \sigma_d;\ \mu_d + n_d * \sigma_d]$ where n_d is a parameter controlling the span over which to perform DVV analysis.

For every set $\beta_k(m, d)$ the variance of the corresponding targets $\sigma_k^2(m, d)$ is computed. The average over the N sets $\beta_k(m, d)$ is divided by the variance of the time series signal

σ_x^2, σ_k gives the inverse measure of predictability, namely target variance σ^{*2}.

$$\sigma^{*2} = \frac{(1/N)\sum_{k=1}^{N}\sigma_k^2}{\sigma_x^2}$$

We note that the delay and the dimension of the phase space are computed automatically by the mutual information [15] and the false nearest neighbors [16] methods respectively.

III. RESULTS

A. Results on synthetic signals

Here we study the evolution of the four methods with variable complexity of synthetic signal, with and without noise. So we plot the value returned by the methods in function of complexity of signal in both cases.

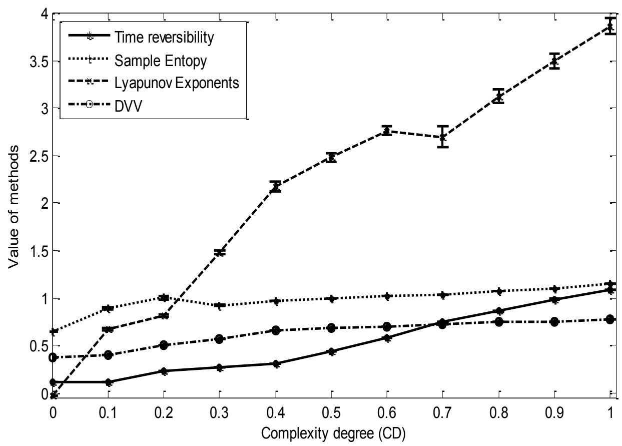

Fig. 1.Evolution of the four methods in function of the complexity of signal generated by the Henon model without noise, plotted with variance bars.

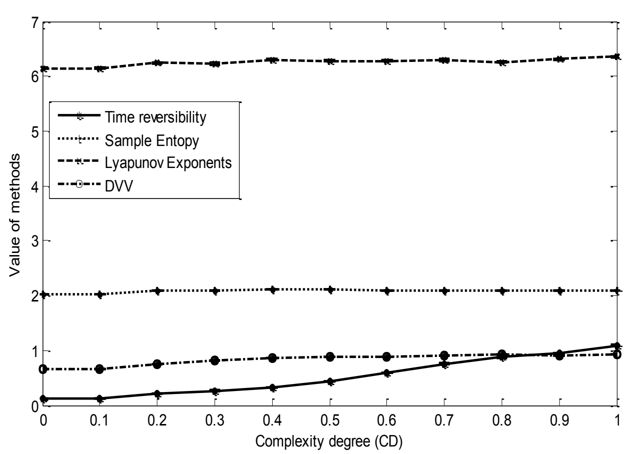

Fig. 2.Evolution of the four methods in function of the complexity of the signal generated by Henon model with noise: SNR=5 db, plotted with variance bars.

In both figures the x-axis is the complexity degree of the Henon model ranging from 0 to 1, the y-axis is the value yielded by the method. It is clear from the results that in the case with no noise the four methods evolve well and increase in relation to complexity (fig. 1). In this case, all methods present an acceptable sensitivity to varying complexity, the best ones being Lyapunov Exponents and Time reversibility. Indeed, they present a greater slope of evolution with varying complexity, than Sample Entropy and DVV. But, in terms of variance, Time reversibility method reveals more precision than Lyapunov exponents as evidenced with the variance bars in figure 1.

In the presence of intense noise (SNR 5dB) (fig. 2), only the Time reversibility method still reflects the underlying change in the complexity of the signal with a very low variance. However it appears that the slope of the curve (sensitivity) of Time reversibility method in noisy case (fig. 2) is lower than the slope (sensitivity) in normal case (fig. 1).

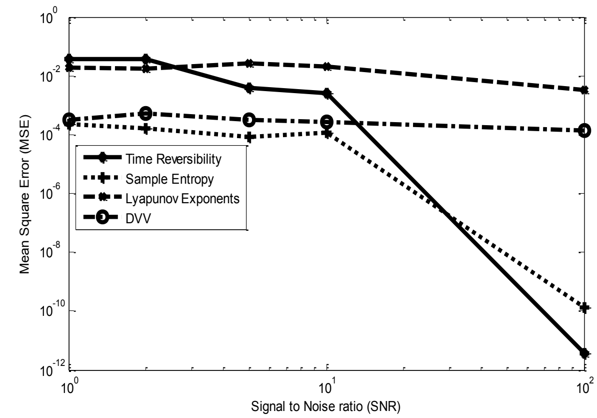

Fig. 3.A logarithmic plot of the mean square error of the four methods as a function of Signal to Noise Ratio for synthetic signals generated by the Henon model: SNR=[1,2,5,10,Inf].

We also investigated the effect of noise on the stability and accuracy of these methods. Figure 3 shows the logarithm of the MSE of the methods (y-axis) with different SNR (logarithm of Signal to Noise Ratio, x-axis) for synthetic signals generated by Henon model. The complexity degree of the model is 0.8 in all cases.

We observe on figure. 3 that with the change of SNR, the MSE of DVV and Lyapunov Exponents methods have approximately the same appearance: they remain constant when SNR changes. Time reversibility and Sample Entropy decrease when SNR increases. The Sample Entropy begin with a very low MSE = $2.27*10^{-4}$ at SNR = 1db and decreases to reach finally a MSE = $1.32*10^{-10}$ at SNR = Inf (fig. 3). Time reversibility methods start with MSE = 0.0383 for SNR= 1db and go on decreasing with increasing SNR to reach a very low MSE = $3.69*10^{-12}$ for SNR = Inf (fig .3).

B. Application to real EHG signals

The different methods were applied to real uterine EMG signals. The Receiver Operating Characteristic (ROC) curves were computed to differentiate between pregnancy and labor contractions. The ROC curves obtained with the different methods are depicted figure 4. The characteristics of all ROC curves are presented in Table I. The best method for the prediction of labor is Time reversibility which presents highest sensitivity (0.86), specificity (0.72), accuracy (ACC) (79.13) and Matthews Correlation Coefficient (MCC) (0.588). The performance in correct classification of labor increases markedly from Area Under

Curve AUC=0.478 with Sample Entropy to 0.842 with Time reversibility.

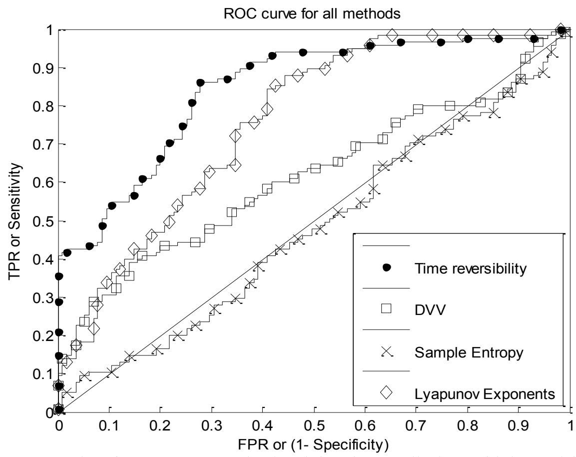

Fig. 4.Example of ROC curves obtained for the prediction of labor with the four different nonlinear methods.

TABLE I
COMPARISON OF ROC CURVES FOR LABOR PREDICTION

Parameter	AUC	ACC	MCC	Specificity	Sensitivity
Time reversibility	0.842	79.13	0.588	0.721	0.860
Sample Entropy	0.478	51.30	0.027	0.382	0.643
Lyapunov Exponent	0.758	70	0.402	0.643	0.756
DVV	0.615	59.13	0.182	0.582	0.600

IV. DISCUSSION

A comparison between four nonlinear methods (Time reversibility, Sample Entropy, Lyapunov Exponents and Delay Vector Variance) was done on synthetic signals generated by nonlinear stationary model (Henon) in order to test their sensitivity to the change in signal complexity, in normal and noisy conditions. The originality in this work that differs from previous work is the study of the evolution of methods with complexity change and of the effect of noise on the method sensitivity. For a given level of complexity, we also show the effect of different SNR on the accuracy of methods.

All four methods were found to reflect correctly the increasing complexity of the signals. But time reversibility was found to be the least sensitive to noise, both in terms of a good sensitivity to complexity evolution for higher noise level than the other methods, and also in terms of low variance and MSE in the presence of noise.

In this paper, we also present results obtained by using nonlinear methods for labor/pregnancy classification of EHG bursts. Comparison between the methods indicates that Time reversibility is clearly most able to classify correctly pregnancy and labor contractions than the other methods.

As further study, we think that if we adapt the surrogates to our signal (Pregnancy, Labor) we can increase the classification rate. Therefore, in future work, we will compare the results obtained by using surrogate data in complement to the application of these methods. The present problem with surrogates is the important computational cost of the method.

V. CONCLUSION

A comparison of different nonlinear methods was performed to study their performance and sensitivity to signal complexity, with and without noise added to synthetic signals. Nonlinear methods were then applied on a set of uterine electrical bursts recorded during pregnancy and labor. The results indicate that Time reversibility is a powerful tool to classify pregnancy and labor signals. This may be related to its good sensitivity and to its robustness (evidenced on synthetic signals), which makes it a good candidate for real, usually noisy, signals. From clinical point of view, we will then attempt to use these findings to predict normal and then preterm labors.

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