



**HAL**  
open science

## Performance analysis of four nonlinearity analysis methods using a model with variable complexity and application to uterine EMG signals.

Ahmad Diab, Mahmoud Hassan, Catherine Marque, Brynjar Karlsson

### ► To cite this version:

Ahmad Diab, Mahmoud Hassan, Catherine Marque, Brynjar Karlsson. Performance analysis of four nonlinearity analysis methods using a model with variable complexity and application to uterine EMG signals.. *Medical Engineering & Physics*, 2014, 36 (6), pp.761-7. 10.1016/j.medengphy.2014.01.009 . inserm-00995890

**HAL Id: inserm-00995890**

**<https://inserm.hal.science/inserm-00995890v1>**

Submitted on 27 May 2014

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Performance analysis of four nonlinearity analysis methods using a model**  
2 **with variable complexity and application to uterine EMG signals**

3 Ahmad Diab<sup>a,b,\*</sup>, Mahmoud Hassan<sup>c</sup>, Catherine Marque<sup>a</sup> and Brynjar Karlsson<sup>b</sup>

4 <sup>a</sup>UMR CNRS 7338, Biomécanique et Bio-ingénierie, Université de Technologie de Compiègne, Compiègne,  
5 France

6 <sup>b</sup>School of Science and Engineering, Reykjavik University, Reykjavik, Iceland

7 <sup>c</sup>Laboratoire Traitement du Signal et de L'Image, INSERM, Université de Rennes1, Campus de Beaulieu,  
8 Rennes, France.

9 E-mail: ahmad.diab@utc.fr (A.Diab), mahmoud.hassan@univ-rennes1.fr (M.Hassan), catherine.marque@utc.fr  
10 (C. Marque), brynjar@ru.is (B. Karlsson).

11 **Abstract**

12 Several measures have been proposed to detect nonlinear characteristics in time series. Results on time  
13 series, multiple surrogates and their z-score are used to statistically test for the presence or absence of  
14 non-linearity. The z-score itself has sometimes been used as a measure of nonlinearity. The sensitivity  
15 of nonlinear methods to the nonlinearity level and their robustness to noise have rarely been evaluated  
16 in the past. While surrogates are important tools to rigorously detect nonlinearity, their usefulness for  
17 evaluating the level of nonlinearity is not clear. In this paper we investigate the performance of four  
18 methods arising from three families that are widely used in non-linearity detection: statistics (Time  
19 reversibility), predictability (Sample Entropy, Delay Vector Variance) and chaos theory (Lyapunov  
20 Exponents). We used sensitivity to increasing complexity and the Mean square Error (MSE) of Monte  
21 Carlo instances for quantitative comparison of their performances. These methods were applied to a  
22 Henon nonlinear synthetic model in which we can vary the complexity degree (*CD*). This was done  
23 first by applying the methods directly to the signal and then using the z-score (surrogates) with and  
24 without added noise. The methods were then applied to real uterine EMG signals and used to

25 distinguish between pregnancy and labor contraction bursts. The discrimination performances were  
26 compared to linear frequency based methods classically used for the same purpose such as Mean  
27 Power Frequency (MPF), Peak Frequency (PF) and Median Frequency (MF). The results show  
28 noticeable difference between different methods, with a clear superiority of some of the nonlinear  
29 methods (Time reversibility, Lyapunov exponents) over the linear methods. Applying the methods  
30 directly to the signals gave better results than using the z-score, except for Sample Entropy.

### 31 **Keywords**

32 Nonlinear time series analysis, uterine electromyogram, contraction discrimination, surrogates.

### 33 **I. Introduction**

34 One of the most common ways of obtaining information on neurophysiologic systems is to study the  
35 features of the signal(s) using time series analysis techniques. This traditionally rely on linear methods  
36 in both time and frequency domains [1]. Unfortunately, these methods cannot give information about  
37 purely nonlinear features of the signal. Due to the intrinsic nonlinearity of most biological systems,  
38 these nonlinear features may be present in physiological data and even be a characteristic of major  
39 interest. Recently, much attention has been paid to the use of nonlinear analysis techniques for the  
40 characterization of a biological signal [2]. Indeed, this type of analysis gives information about the  
41 nonlinear features of these signals, which arise from the underlying physiological processes, many of  
42 which have complex behavior. There is a growing literature reporting nonlinear analysis of various  
43 biosignal types (EEG [3], ECG [4], HRV [5] and EMG [6]).

44 The EHG or electrohysterogram (electrical uterine activity recorded on woman's abdomen) has been  
45 widely studied [7], [8], [9], [10], [11]. Nonlinear characteristics have been observed in the EHG  
46 and some success has been achieved by using these characteristics to obtain information of  
47 potential clinical usefulness. Radomski et al. show that nonlinear analysis of EHG based on the sample  
48 entropy statistic could differentiate dynamic states of uterine contractions [12]. A comparison between  
49 linear and nonlinear analysis with different conditions was done in [13]. It was concluded that median  
50 frequency is the best method among linear methods and that sample entropy is the best method among

01 nonlinear methods for term/preterm EHG contractions classification. Sample entropy is superior to  
02 median frequency, which indicates that nonlinear analysis is more suitable than linear analysis for  
03 studying EHG signals. In [14] the progress of labor was evaluated using sample entropy. Our team has  
04 examined nonlinear EHG analysis methods. Our results confirm the presence of nonlinearity in EHG  
05 signals. This character of the signals is useful in discriminating between pregnancy and labor  
06 contractions [15], [2], [16]. Practical disadvantages of the nonlinear analysis methods have been  
07 reported in [16]. They include excessive calculation time due to surrogates analysis and promising but  
08 inconclusive results due to the small amount of data that can practically be used due to heavy  
09 calculation times.

10 This paper presents work that extends previous work done in our group in comparing Approximate  
11 Entropy, Correntropy and Time reversibility [16]. In this work we implemented additional nonlinear  
12 analysis methods (delay vector variance, Lyapunov exponents) and new ways of testing them. We  
13 also used a larger database of real signals than in the previous work and we investigated the sensitivity  
14 of the methods to the varying complexity of signals and their robustness. The kind of sensitivity and  
15 robustness analyses of non-linearity measures presented in this paper, are rare or absent in the  
16 literature.

17 Four nonlinear methods: Time reversibility [17], Sample Entropy [18], Delay Vector Variance [19]  
18 and Lyapunov Exponents [20] were used in this work. Sensitivity of these methods to the complexity  
19 degree ( $CD$ ) of a signal as well as robustness analysis were done on Henon model synthetic signals  
20 where  $CD$  can be controlled. The sensitivity to  $CD$  was first studied using the direct value provided by  
21 the method. It was then studied using surrogates and z-score, as the measure permitting evaluation of  
22 the nonlinearity. One objective of this study is to show which method(s) is most sensitive to the  
23 change of signal complexity. A second objective is to determine whether the use of surrogates gives  
24 better overall results than the direct application of the methods. This is of major practical importance  
25 for clinical application, as the generation of surrogates is very computationally expensive. The  
26 methods are also compared using the Mean square error (MSE) of the method results for 30 Monte  
27 Carlo instances of the signal. Finally, these non-linear methods are compared to three linear frequency

based characteristics of the signal, MPF, PF and MF, when applied to real EHG signals, in order to discriminate pregnancy and labor contractions.

## II. Materials and Methods

### A) Data

#### 1. Synthetic signals

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  $Y_t$  and  $X_t$  represent dynamical variables,  $CD$  is the complexity degree and  $c$  is the dissipation parameter. In this paper we use  $c = 1$  as in [21] and  $CD \in [0, 1]$  to change the model complexity [22] (Figure 1). The number of generated points is fixed to 1000. For the robustness analysis, we add to the synthetic signals a white Gaussian noise with the same duration, with a fixed 5db SNR with  $CD$  varying between 0 and 1 with a step 0.1. In the Monte Carlo analysis, we use 30 signals generated for each  $CD$  value.

#### 2. Real signals

EHG signals were recorded from 38 subjects using a 4x4 electrode matrix located on the subject's abdomen (Figure 2), during one hour either at rest (woman lying on a bed) or during labor. One signal channel (bipolar vertical 7: BP7), located on the median vertical axis of the uterus was used for subsequent analysis (see [23] for details). After segmentation we obtained 115 labor bursts (recorded during delivery) and 174 pregnancy bursts (recorded more than 24 hours before delivery).

### B) Non-linear Analysis Methods

#### 1. Statistics family

### 98 a) Time reversibility

99 A time series is said to be reversible only if its probabilistic properties are invariant with respect to  
100 time reversal. Time irreversibility can be taken as a strong signature of nonlinearity [17]. In this paper  
101 we used the simplest method, described in [24] to compute the time reversibility of a signal  $S_n$ :

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

102 where  $N$  is the signal length and  $\tau$  is the time delay.

## 103 2. Chaos theory family

### 104 a) Lyapunov Exponents

105 Lyapunov exponent (LE) is a quantitative indicator of system dynamics, which characterizes the  
106 average convergence or divergence rate between adjacent tracks in phase space [20]. We used the  
107 method described in [13] to compute LE:

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

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

## 110 3. Predictability family

### 111 a) Sample Entropy

112 Sample Entropy (*SampEn*) is the negative natural logarithm of the conditional probability that a  
113 dataset of length  $N$ , having repeated itself for  $m$  samples within a tolerance  $r$ , will also repeat itself for  
114  $m+1$  samples. Thus, a lower value of *SampEn* indicates more regularity in the time series [18]. We  
115 used the method described in [12] to compute *SampEn* :

116 For a time series of  $N$  points,  $x_1, x_2, \dots, x_N$ , we define subsequences, also called template vectors, of  
 117 length  $m$ , given by:  $y_i(m) = (x_i, x_{i+1}, \dots, x_{i+m-1})$  where  $i = 1, 2, \dots, N-m+1$ .

118 Then the following quantity is defined:  $B_i^m(r)$  as  $(N-m-1)^{-1}$  times the number of vectors  $X_j^m$  within  $r$   
 119 of  $X_i^m$ , where  $j$  ranges from  $1$  to  $N-m$ , and  $j \neq i$ , to exclude self-matches, and then define:

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

120 Similarly, we 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  $j$   
 121 ranges from  $1$  to  $N-m$ , where  $j \neq i$ , and set

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

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

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

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

### 126 *b) Delay Vector Variance*

127 We use the measure of unpredictability  $\sigma^{*2}$  described in [25]:

128 Time series can be represented in phase space using time delay embedding. When time delay is  
 129 embedded into a time series, it can be represented by a set of delay vectors (DVs) of a given  
 130 dimension  $m$ . The dimension of the delay vectors can then be expressed as  $X(k) = [x_{(k-m\tau)} \dots x_{(k-\tau)}]$ ,  
 131 where  $\tau$  is the time lag. For every DV  $X(k)$ , there is a corresponding target, namely the next sample  $x_k$ .  
 132 A set  $\beta_k(m, d)$  is generated by grouping those DVs that are within a certain Euclidean distance  $d$  to  
 133 DV  $X(k)$ . This Euclidean distance will be varied in a standardized manner with respect to the

134 distribution of pairwise distances between DVs. For a given embedding dimension  $m$ , a measure of  
 135 unpredictability  $\sigma^{*2}$  (target variance) is computed over all sets of  $\beta_k$ .

136 The mean  $\mu_d$  and the standard deviation  $\sigma_d$  are computed over all pair wise Euclidean distances  
 137 between DVs given by  $\|x(i) - x(j)\| (i \neq j)$ . The sets  $\beta_k(m, d)$  are generated such that  $\beta_k =$   
 138  $\{x(i) \mid \|x(k) - x(j)\| \leq d\}$  i.e., sets which consist of all DVs that lie closer to  $X(k)$  than a certain  
 139 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  
 140 over which to perform DVV analysis.

141 For every set  $\beta_k(m, d)$  the variance of the corresponding targets  $\sigma_k^2(m, d)$  is computed. The average  
 142 over the  $N$  sets  $\beta_k(m, d)$  is divided by the variance of the time series signal  $\sigma_x^2$ ,  $\sigma_k$  gives the inverse  
 143 measure of predictability, namely target variance  $\sigma^{*2}$ .

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

### 144 C) Surrogates and z-score.

145 The most commonly used null hypothesis considers that a given time series is generated by a Gaussian  
 146 linear stochastic process and collected through a nonlinear measurement static function. Thus  
 147 surrogates must have the same linear properties (autocorrelation and amplitude distribution) as the  
 148 original signal. However, any underlying nonlinear dynamic structure within the original data is  
 149 altered in the surrogates by phase randomization [16].

150 The statistics of significance z-score is,

$$Z_{score} = \frac{|q_0 - \langle q_s(i) \rangle|}{\sigma_q(i)}$$

151 where  $q_0$  stands for the statistic on the original time series,  $\langle q_s(i) \rangle$  for the mean and  $\sigma_q(i)$  for the  
 152 standard deviation of the surrogate, for  $i=1, 2, \dots, M$  (number of generated surrogate). The critical value  
 153 of z-score is 1.96 [26].

154



100

### 106 **III. Results**

#### 107 **A) Results on synthetic signals**

108 In this section we study the evolution of the values generated by the four methods with variable  
109 complexity degree ( $CD$ ) of the Henon synthetic model in four cases; 1) direct application of the  
160 method with no added noise, 2) using surrogates with no added noise, 3) direct application of the  
161 method with added noise and 4) using surrogates with added noise. The added noise is a white  
162 Gaussian noise ( $SNR=5$  db) while  $CD$  varies between 0 and 1, for the Henon model. Our first  
163 objective is to test the sensitivity of the methods to varying  $CD$  for signals with and without noise. The  
164 use of surrogates is computationally very expensive and therefore our second objective is to test if the  
165 use of surrogates improves the method sensitivity or not. .

166 We compare the methods using two criteria, the method's sensitivity to the change of  $CD$  (slope of the  
167 curve "value of the method" vs. " $CD$ ") and the MSE of the method for different values of  $CD$ .

168 Figure 3-A1 presents the mean value for each method (direct method value) as a function of  $CD$   
169 computed from the 30 Monte Carlo instances of the signal generated by the Henon model. Figure 3-  
170 A2 presents the MSE of the methods for each  $CD$ . We see in Figure 3-A1 that in the direct case  
171 without noise, the four methods evolve well but with differences in their sensitivity (slopes). Tr and  
172 LE are more sensitive than the other methods. In Figure 3-A2 we observe that Tr has a much lower  
173 MSE than LE.

174 Figure 3-B1 presents the effect of adding noise ( $SNR=5$ db) on the methods. We notice no significant  
175 slope for the LE and SampEn. The sensitivity of Tr and DVV also decreases with the addition of  
176 noise. In the other hand we find, Figure 3-B2, that DVV and SampEn give the lowest MSE. However  
177 SampEn does not demonstrate any sensitivity to the variation of  $CD$  so this method is useless for the  
178 noisy signal. Tr gives an intermediate MSE and the highest sensitivity when compared to the other  
179 methods when applied to noisy signals.

180 We then applied the methods to the synthetic signals with surrogates using the z-score as measure, in  
181 order to test if the use of surrogates improves the results or not. Figure 3-C1 presents the z-score for  
182 each method versus  $CD$ . We note that all the methods reflect the non-linearity of the signal generated  
183 by the Henon model as theirs z-score are always above 1.96. In terms of sensitivity to  $CD$  variation,  
184 SampEn is the best, but with the highest MSE (Figure 3-C2). Tr presents an acceptable evolution for  
185 lower  $CD$ . But beyond  $CD = 0.4$  an unexpected decrease occurs in the curve and the Tr value remains  
186 constant after  $CD=0.7$ . This method however, gives the lowest MSE (Figure 3-C2). The DVV method  
187 presents an intermediate slope, contrary to the LE that presents no change with  $CD$ . Both DVV and LE  
188 have low MSE under these conditions.

189 The methods were then applied to the signals using again surrogates and z-score but with added noise  
190 (SNR=5db). All the methods still reveal the nonlinearity of the model. Indeed z-score is above 1.96 for  
191 all the methods, except for DVV where it gives a z-score value lower then 1.96 for  $CD$  between 0.4  
192 and 0.6. We can clearly notice an increase in the sensitivity of Tr, Figure 3-D1, compared to the case  
193 in Figure 3-C1. SampEn has a good evolution beyond  $CD = 0.4$  but, on the other hand, it presents a  
194 rapid increase in MSE (Figure 3-D2). The LE and DVV do not evolve as a function of  $CD$  (Figure 3-  
195 D1) and give similar MSE as Tr (Figure 3-D2).

## 196 **B) Results on real signals**

197 The different nonlinear methods were applied to real uterine EMG signals (EHG), first direct  
198 application of the method, and then with surrogates. We also computed three classical linear frequency  
199 based parameters from these real signals. The values were then used to discriminate the pregnancy and  
200 labor contractions. We used ROC curves in order to test the discriminating power of each case.

201 Our first objective was to test if the use of surrogates improves the discrimination of EHG bursts  
202 recorded during Pregnancy or Labor. Our second objective was to compare the performances of linear  
203 and nonlinear methods and to verify that the nonlinear methods reveal the evolution of EHG  
204 characteristics better than the linear ones. The ROC curves obtained with the different methods  
205 without and with use of surrogates are presented Figure 4-B and Figure 4-C respectively. The

206 characteristics of all the ROC curves without and with use of surrogates are presented in Table I and  
207 Table II respectively. From these data, it is clear that nonlinear methods improve the discrimination of  
208 pregnancy and labor signals. Indeed, the highest Area Under Curve AUC (0.842), sensitivity (0.86)  
209 and specificity (0.72) are obtained for the Tr method whatever the nonlinear or linear methods used.  
210 The MPF and LE methods also give an acceptable performance (Figure 4-B) with AUC=0.778 and  
211 AUC=0.758 respectively. The performances in correct discrimination of labor varies markedly from  
212 AUC=0.478 with SampEn to AUC=0.842 with Tr. When surrogates are used, all ROC curves present  
213 approximately the same appearance with the highest AUC=0.650 obtained for SampEn. Using  
214 surrogates we notice that the performance of SampEn improves while that of DVV remains  
215 approximately the same. On the other hand, the performance of Tr and LE seem to decrease with the  
216 use of surrogates. Finally, we can conclude from Figure 4 and Table I that nonlinear methods can  
217 provide better discrimination between pregnancy and labor contractions compared to the linear  
218 methods. Furthermore, even if the use of surrogates improves the performance of some methods, it  
219 does not generally improve the discrimination results.

#### 220 **IV. Discussion and conclusion**

221 We analyzed, quantitatively and as comprehensively as possible, four different nonlinear analysis  
222 methods (Tr, SampEn, DVV and LE). These methods were applied on synthetic signals, in order to  
223 test their sensitivity to the change in signal complexity, in normal and noisy conditions, with or  
224 without using surrogates. All four methods were found to reflect correctly the increasing complexity  
225 of the signals in the noise free case, but with different sensitivities. In the case of added noise and  
226 direct application of the method, as expected, a decrease in the sensitivity of all methods occurred at a  
227 low Signal to Noise Ratio (SNR=5db). Indeed, at this low SNR, none of the methods detected the  
228 varying complexity of the signal, except for Tr, which clearly reflected the increasing non-linearity.  
229 The sensitivity of SampEn increased with the use of surrogates and it gave the highest sensitivity of all  
230 the methods, in the case of surrogate use with no added noise. Indeed SampEn has previously been  
231 shown to be sensitive to many aspects of the signal characteristics, including the sampling rate of the  
232 signal [14], [11]. Unexpected results were obtained in the case of surrogate use and with added noise.

Tr was more sensitive when compared to the previous case, and SampEn still presented a good sensitivity. We noticed that in the case of surrogate use, SampEn gave the highest sensitivity but also had the highest MSE, making it unreliable.

In this paper we also presented results obtained using nonlinear and linear methods for discrimination of EHG bursts recorded during pregnancy and labor. Comparison between the methods indicated that Tr, which is a nonlinear method, applied without using surrogates is clearly better in discriminating correctly pregnancy and labor contractions than the other methods. We can see also that the use of surrogates improves the performance of some methods like SampEn. These results confirm the results obtained during the study on synthetic signal, since the sensitivity of SampEn increases if surrogates are used, a posteriori justifying the use of the Henon model.

To sum up, the main findings of this study are the following: (i) Some of the studied methods are insensitive to varying signal complexity; (ii) SampEn performance depends on the use of surrogates; (iii) Generally speaking, none of the studied methods performed best in all the studied situations; (iv) Tr is very sensitive to change of model complexity, giving average or good performances, associated with the lowest MSE in most situations.

This leads to the conclusion that, of the four methods tested, Tr performed best for our application on real EHG. Indeed Tr deals robustly with real, usually noisy, signals and has a good sensitivity to complexity, one of the EHG characteristics that permits discrimination of uterine contraction efficiency. Using surrogates and the z-score, as a measure of nonlinearity, does not seem to bring any improvement to Tr. Therefore we will not use them for further work on EHG when using Tr.

There are some weaknesses in our study of which we are aware and aim to improve. Tr is dependent on the length of the signal and on the choice of the time delay ( $\tau$ ) and we aim to find a method to optimize these parameters. In further work we also aim to use all of the available bipolar channels (VA1,...,VA12) instead of only one channel, as in this work. This has been shown to dramatically increase the discrimination rate as evidenced in prior work [27].

**Acknowledgment:**

209 The authors wish to thank Dr. Jeremy Terrien for his helpful advice.

260 **Conflict of interest**

261 No conflict of interest.

262 **Sources of funding for research**

263 French Ministry of Research, French ministry of foreign affair and the EraSysBio+ program.

264 **Ethical Approval**

265 The measurements in Iceland were approved by the relevant ethical committee (VSN 02-0006-V2),

266 those in France approved by the regional ethical committee (ID-RCB 2011-A00500-41) of Amiens

267 Hospital.

268

269

270

271

272

273

274

275

276

277

278

279 **References:**

- 280 [1] Bendat, J.S. and Piersol, A.G., *Random Data Analysis and Measurement Procedures.*  
281 *Measurement Science and Technology*, 2000. **11**(12): p. 1825.
- 282 [2] Hassan, M., Terrien, J., Alexandersson, A., Marque, C., and Karlsson, B., *Nonlinearity of EHG*  
283 *signals used to distinguish active labor from normal pregnancy contractions.* in *Conf Proc IEEE*  
284 *Eng Med Biol Soc.* 2010, p. 2387-2390.
- 285 [3] Takahashi, T., Cho, Raymond Y., Mizuno, T., Kikuchi, M., Murata, T., Takahashi, K., and Wada,  
286 Y., *Antipsychotics reverse abnormal EEG complexity in drug-naive schizophrenia: A multiscale*  
287 *entropy analysis.* *NeuroImage*, 2010. **51**(1): p. 173-182.
- 288 [4] Shiogai, Y., Stefanovska, A., and McClintock, P.V.E, *Nonlinear dynamics of cardiovascular*  
289 *ageing.* *Physics Reports*, 2010. **488**(2-3): p. 51-110.
- 290 [5] Mohebbi, M. and Ghassemian, H., *Prediction of paroxysmal atrial fibrillation based on non-*  
291 *linear analysis and spectrum and bispectrum features of the heart rate variability signal.*  
292 *Computer Methods and Programs in Biomedicine*, 2012. **105**(1): p. 40-49.
- 293 [6] Xie, H.-B., Zheng, Y.-P., Guo, J.-Y., and Chen, X., *Cross-fuzzy entropy: A new method to test*  
294 *pattern synchrony of bivariate time series.* *Information Sciences*, 2010. **180**(9): p. 1715-1724.
- 295 [7] Lucovnik, M., Kuon, R. J., Chambliss, L. R., Maner, W. L., Shi, S. Q., Shi, L., Balducci, J.,  
296 Garfield, R. E., *Use of uterine electromyography to diagnose term and preterm labor.* *Acta*  
297 *Obstet Gynecol Scand*, 2011. **90**(2): p. 150-7.
- 298 [8] Garfield, R.E., Maner, W. L., MacKay, L. B., Schlembach, Dietmar, Saade, G. R., *Comparing*  
299 *uterine electromyography activity of antepartum patients versus term labor patients.* *American*  
300 *Journal of Obstetrics and Gynecology*, 2005. **193**(1): p. 23-29.
- 301 [9] Schlembach, D., Maner, W. L., Garfield, R.E., Maul, H., *Monitoring the progress of pregnancy*  
302 *and labor using electromyography.* *Eur J Obstet Gynecol Reprod Biol*, 2009. **144 Suppl 1**: p.  
303 S33-9.
- 304 [10] Hassan, M., Alexandersson, A., Terrien, J., Muszynski, C., Marque, C., Karlsson, B., *Better*  
305 *pregnancy monitoring using nonlinear propagation analysis of external uterine*

- 306 *electromyography*. IEEE Transactions on Biomedical Engineering, April 2013, Vol **60(4)**: p.  
307 1160 - 1166.
- 308 [11] Diab, A., Hassan, M., Karlsson, B., Marque, C., *Effect of decimation on the classification rate of*  
309 *nonlinear analysis methods applied to uterine EMG signals*. IRBM journal, 2013 (In press).
- 310 [12] Radomski, D., Grzanka, A., Graczyk, S., and Przelaskowski, A., *Assessment of Uterine*  
311 *Contractile Activity during a Pregnancy Based on a Nonlinear Analysis of the Uterine*  
312 *Electromyographic Signal*. Information Technologies in Biomedicine, 2008: p. 325-331.
- 313 [13] Fele-Zorz, G., Kavsek, G., Novak-Antolic, Z., and Jager, F., *A comparison of various linear and*  
314 *non-linear signal processing techniques to separate uterine EMG records of term and pre-term*  
315 *delivery groups*. Med Biol Eng Comput, 2008. **46(9)**: p. 911-22.
- 316 [14] Vrhovc, J., *Evaluating the progress of the labour with sample entropy calculated from the*  
317 *uterine EMG activity*. Elektrotehnikski vestnik-Electrotechnical Review, 2009. **76(4)**: p. 165-170.
- 318 [15] Diab, A., Hassan, M., Marque, C., and Karlsson, B., *Quantitative performance analysis of four*  
319 *methods of evaluating signal nonlinearity: Application on uterine EMG signals*, in *Conf Proc*  
320 *IEEE Eng Med Biol Soc*. 2012.
- 321 [16] Hassan, M., Terrien, J., Karlsson, B., and Marque, C., *Comparison between approximate entropy,*  
322 *correntropy and time reversibility: Application to uterine EMG signals*, Medical Engineering &  
323 Physics (MEP), oct 2011, vol. 33, p. 980-986.
- 324 [17] Diks, C., van Houwelingen, J. C., Takens, F., and DeGoede, J., *Reversibility as a criterion for*  
325 *discriminating time series*. Physics Letters A, 1995. **201(2-3)**: p. 221-228.
- 326 [18] Richman, J.S. and Moorman, J.R., *Physiological time-series analysis using approximate entropy*  
327 *and sample entropy*. American Journal of Physiology-Heart and Circulatory Physiology, 2000.  
328 **278(6)**: p. H2039-H2049.
- 329 [19] Gautama, T., Mandic, D.P., and Van Hulle, M.M., *The delay vector variance method for*  
330 *detecting determinism and nonlinearity in time series*. Physica D: Nonlinear Phenomena, 2004.  
331 **190(3-4)**: p. 167-176.

- 332 [20] Wolf, A., Swift, Jack B., Swinney, Harry L., Vastano, and John A., *Determining Lyapunov*  
333 *exponents from a time series*. Physica D: Nonlinear Phenomena, 1985. **16**(3): p. 285-317.
- 334 [21] Pincus, S.M., *Approximate Entropy as a Measure of System-Complexity*. Proceedings of the  
335 National Academy of Sciences of the United States of America, 1991. **88**(6): p. 2297-2301.
- 336 [22] Casas, G.A. and Rech, P.C., *Multistability annihilation in the Hénon map through parameters*  
337 *modulation*. Communications in Nonlinear Science and Numerical Simulation, 2012. **17**(6): p.  
338 2570-2578.
- 339 [23] Karlsson, B., Terrien, J., Guðmundsson, V., Steingrímisdóttir, T., and Marque, C., *Abdominal*  
340 *EHG on a 4 by 4 grid: mapping and presenting the propagation of uterine contractions*. in 11th  
341 Mediterranean Conference on Medical and Biological Engineering and Computing, 2007, p. 139-  
342 425, Ljubljana, Slovenia.
- 343 [24] Schreiber, T. and Schmitz, A., *Surrogate time series*. Phys. D, 2000. **142**(3-4): p. 346-382.
- 344 [25] Kuntamalla S., R.L., *The Effect of Aging on Nonlinearity and Stochastic Nature of Heart Rate*  
345 *Variability Signal Computed using Delay Vector Variance Method*. International Journal of  
346 Computer Applications, 2011. **Volume 14**(No.5): p. 40-44.
- 347 [26] Slađana, S., *Surrogate data test for nonlinearity of the rat cerebellar electrocorticogram in the*  
348 *model of brain injury*. Signal Processing, 2010. **90**(12): p. 3015-3025.
- 349 [27] Hassan, M., Terrien, J., Alexandersson, A., Marque, C., and Karlsson, B., *Improving the*  
350 *classification rate of labor vs. normal pregnancy contractions by using EHG multichannel*  
351 *recordings*. in Conf Proc IEEE Eng Med Biol Soc. 2010, p. 4642-4645.

352  
353

354

355

356

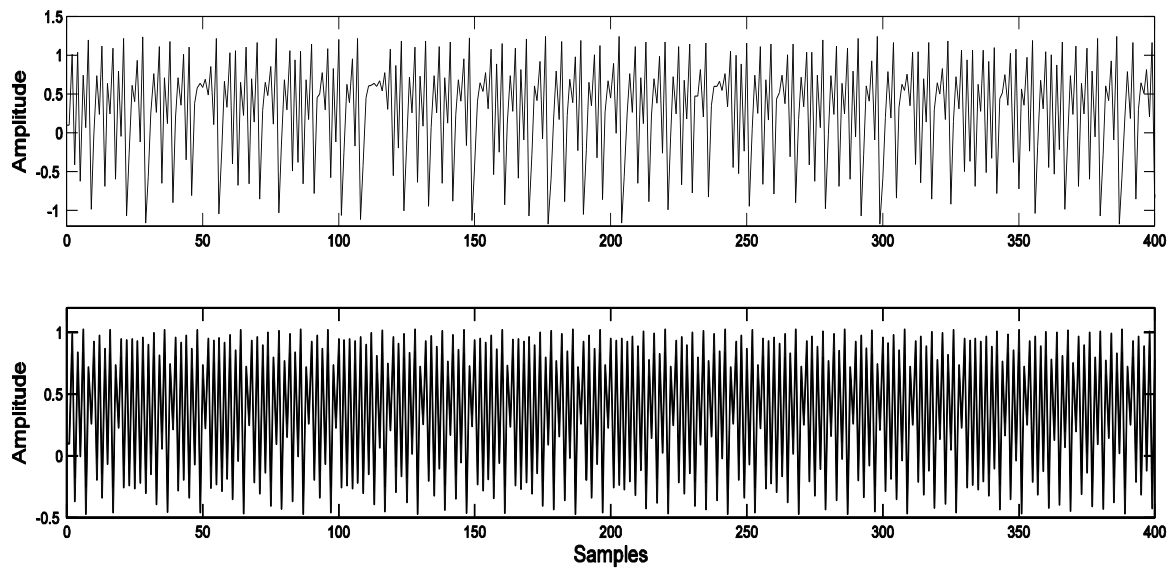
357

358

359



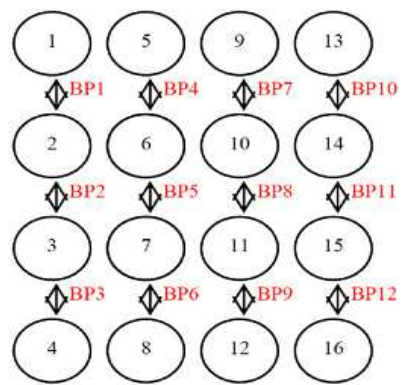
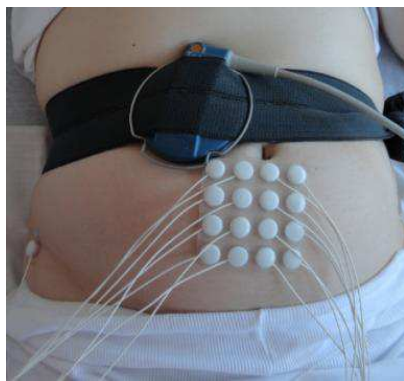
36.  
361  
362  
363  
364  
365  
366  
367  
368  
369  
37.  
371  
372



373  
374  
375  
376  
377  
378  
379

Fig. 1. Simulated signal generated using Henon model with different complexity degrees ( $CD$ ). Top:  $CD = 0.1$ , Bottom:  $CD = 0.9$

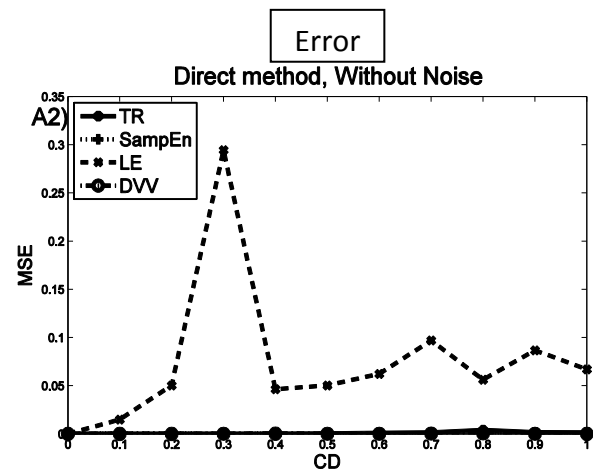
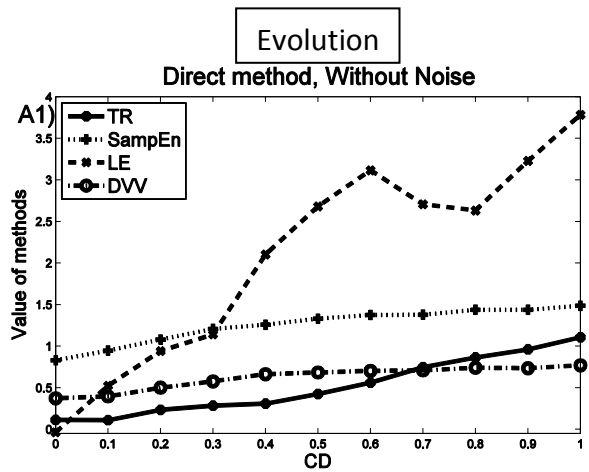
۳۸۰  
۳۸۱  
۳۸۲  
۳۸۳  
۳۸۴  
۳۸۵  
۳۸۶  
۳۸۷



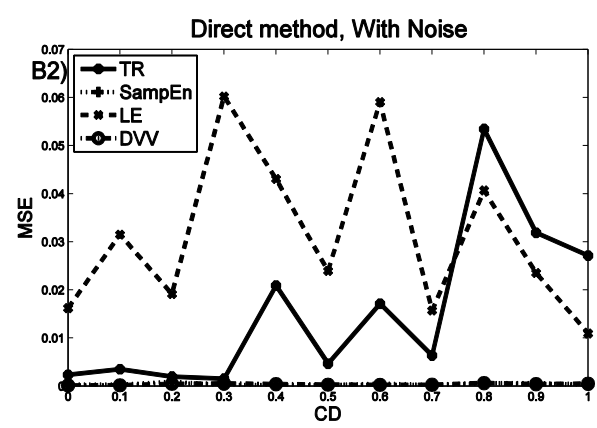
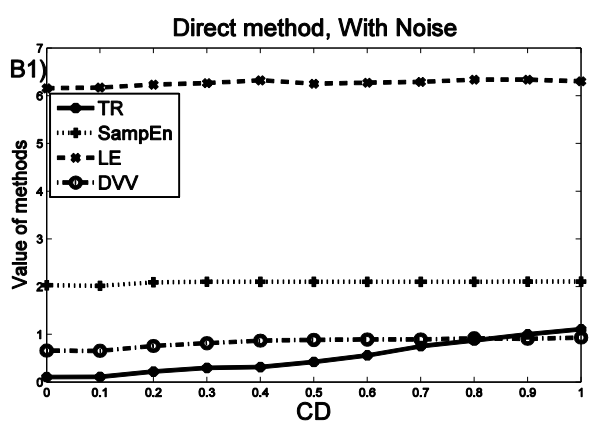
۳۸۸  
۳۸۹

Fig. 2. Electrode placement (left), monopolar configuration and the corresponding bipolar signals BPi (right).

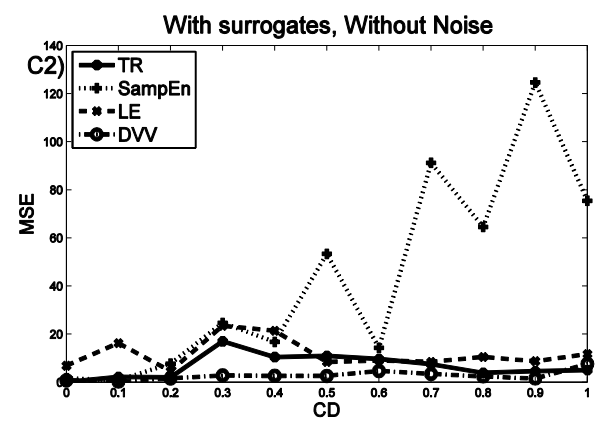
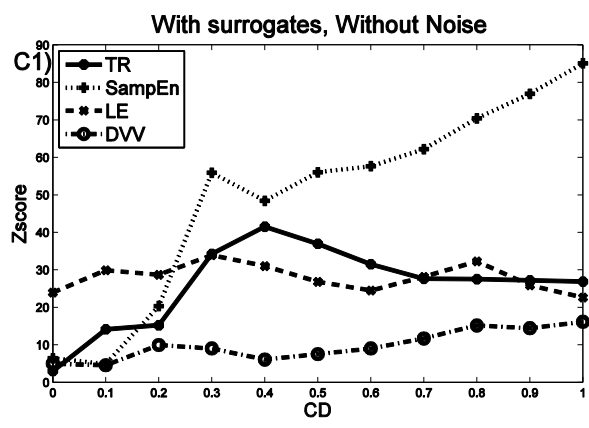
۳۹۰



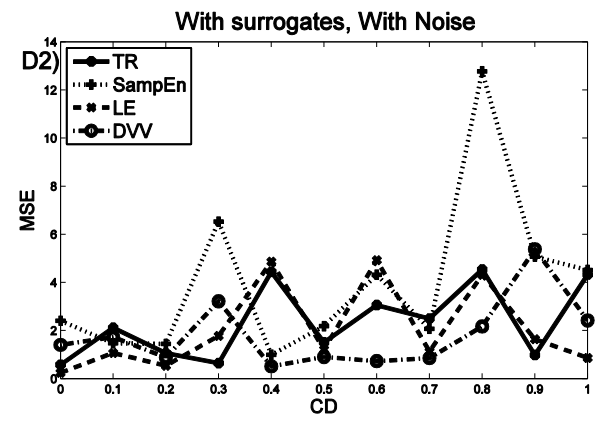
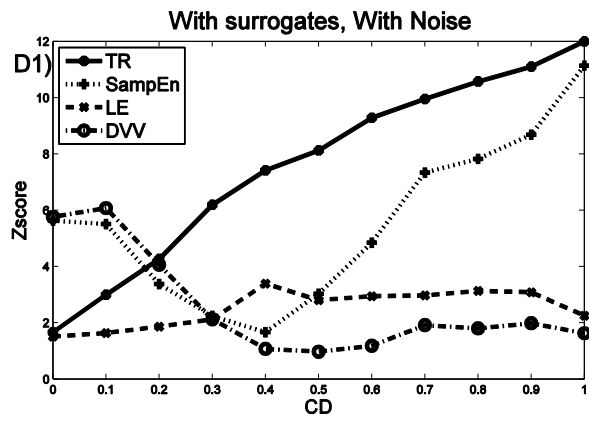
۳۹۱



۳۹۲



۳۹۳



۳۹۴

۳۹۵

۳۹۶

Fig. 3. Results obtained for Henon model using Monte-carlo simulation. On the left: Evolution of the methods with variable complexity in different cases. On the right: MSE of the methods function of complexity degree in different cases. (A) Direct method with no added noise, (B) Direct method with added noise, (C) With surrogate use and no added noise, (D) With surrogate use and added noise.

397

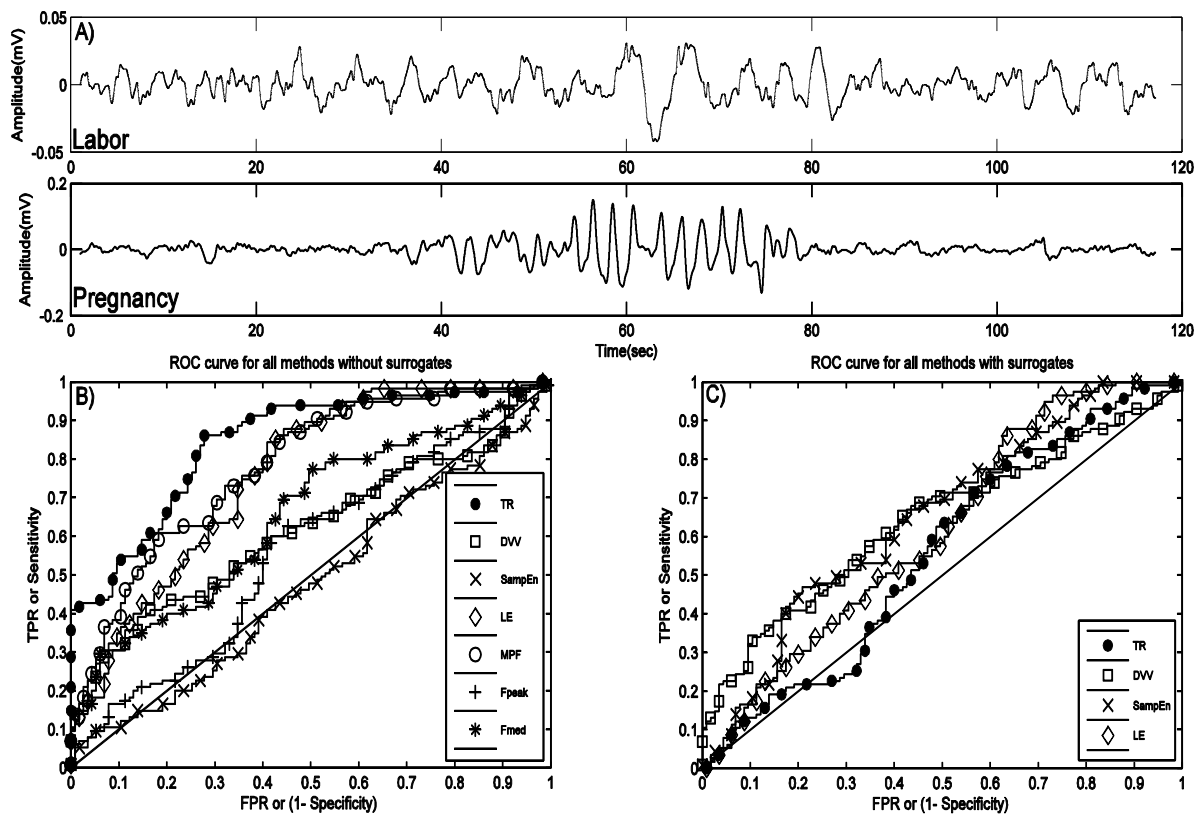
398

399

400

401

402



403

404

405

Fig. 4. Example of ROC curves obtained for the detection of labor with the different linear and nonlinear methods. (A) Real Pregnancy and Labor contractions, (B) Direct method, (C) With surrogate use.

406  
407  
408  
409  
410  
411  
412  
413  
414  
415  
416  
417  
418  
419  
420  
421  
422  
423  
424  
425  
426  
427  
428  
429

TABLE I (Direct method)  
Comparison of ROC curves for labor detection

Parameter	AUC	Specificity	Sensitivity
Time reversibility	<b>0.842</b>	<b>0.721</b>	<b>0.860</b>
Sample Entropy	0.478	0.382	0.643
Lyapunov Exponent	0.758	0.643	0.756
Delay Vector Variance	0.615	0.582	0.600
Mean Power Frequency	<b>0.778</b>	<b>0.678</b>	<b>0.730</b>
Peak Frequency	0.561	0.582	0.600
Median Frequency	0.654	0.556	0.704

TABLE II (with surrogate use)  
 Comparison of ROC curves for labor detection

Parameter	AUC	Specificity	Sensitivity
Time reversibility	0.560	0.513	0.626
Sample Entropy	<b>0.650</b>	<b>0.593</b>	<b>0.643</b>
Lyapunov Exponent	0.614	0.591	0.530
DVV	0.642	0.573	0.669