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Windowed Multivariate Autoregressive Model improving Classification of Labor vs. Pregnancy Contractions

Brynjar Karlsson, Mahmoud Hassan and Catherine Marque

Abstract— **Analyzing the propagation of uterine electrical activity is poised to become a powerful tool in labor detection and for the prediction of preterm labor. Several methods have been proposed to investigate the relationship between signals recorded externally from several sites on the pregnant uterus. A promising recent method is the multivariate autoregressive (MVAR) model. In this paper we proposed a windowed (time varying) version of the multivariate autoregressive model, called W-MVAR, to investigate the connectivity between signals while still respecting their non-stationary characteristics. The proposed method was tested on synthetic signals as well as applied to real signals. The comparison between the two methods on synthetic signals showed the superiority of W-MVAR to detect connectivity even if it is non-stationary. The application of W-MVAR on multichannel real uterine signals show that the proposed method is a good tool to distinguish non-labor and labor signals. These results are very promising and can very possibly have important clinical applications in labor detection and preterm labor prediction.**

I. Introduction

Multichannel recordings are necessary to investigate physiological phenomena that have an extended range over an organ or an organ system such as the brain, skeletal muscles or the uterus. Recently most of the actors in the field of uterine EMG or electrohysterogram (EHG) have adopted multi electrode configuration for measurement and concentrate on the study of how the uterus synchronizes and starts to operate as a whole as labor progresses. The methods most often used in the literature for preterm labor prediction use only the analysis of the high frequency content of the EHG [1, 2] which is thought to be primarily related to uterine cell excitability [3]. These methods are however not currently used in routine practice as far as we know. Recently, studies using propagation analysis in the view of detection labor and prediction preterm labor have started to appear. These methods include the use of nonlinear correlation analysis [4], phase synchronization [5] and more recently the use of propagation velocity (PV) to classify labor and non-labor signals [6]. These methods have shown the clear superiority of propagation parameters over the frequency based excitability parameters to detect labor.

A new way to analyze relationships between multichannel signals that is based on estimated coefficients from Multivariate Autoregressive model (MVAR) of the signals has recently been presented. The main advantage of MVAR method is to take into account of the connectivity between all the signals and not between only two signals. The main connectivity estimators based on the MVAR model are the Granger causality index (GCI), the directed transfer function (DTF) and the Partial Directed Coherence (PDC). These methods have mostly been applied in various fields of brain research [7, 8] and have not been applied on the EHG signals before. A drawback of the MVAR method is that it assumes that the signals are stationary which not the case of the majority of biosignals.

In this work we propose a windowing (time-varying) version of MVAR called W-MVAR aimed to respect the non-stationary characteristics of EHG signals. We compare W-MVAR with the classical MVAR on synthetic signals as well as on real EHG signals in the view of distinguishing between non labor and labor signals.

II. Materials and Methods

A. MVAR

For a multichannel signal X with m dimensions, the multivariate autoregressive (MAR) process can be defined as:

$$\begin{pmatrix} x_1(k) \\ x_2(k) \\ \cdot \\ \cdot \\ \cdot \\ x_m(k) \end{pmatrix} = \sum_{r=1}^{p} A_r \begin{pmatrix} x_1(k-r) \\ x_2(k-r) \\ \cdot \\ \cdot \\ \cdot \\ x_m(k-r) \end{pmatrix} + \begin{pmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_m(k) \end{pmatrix} \tag{1}$$

where $\varepsilon_i(k)$ represents independent Gaussian white noise with covariance matrix Σ and $A_1,\ldots A_p$ are the coefficient matrix (m x m). This time domain representation can be translated to frequency domain by computing the power spectral density matrix:

$$S(f)=H(f)\Sigma H^h(f) \tag{2}$$

Where h denotes the Hermitian transpose. H is the transfer function defined as:

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B. Karlsson is with the School of Science and Engineering, Reykjavik University, Reykjavik, 101 Iceland (corresponding author: +354-599 83256490; fax: +354 599; e-mail: brynjar@ru.is).
M. Hassan is with the Laboratoire Traitement du Signal et de L'Image, INSERM, Université de Rennes1, Campus de Beaulieu, 35042 Rennes Cedex, France.
C. Marque is with CNRS UMR 7338 Biomécanique et Bio-ingénierie, Université de Technologie de Compiègne, 60200 Compiègne, France.

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$$H(f)=\bar{A}^{-1}(f)=[I-A(f)]^{-1} \quad (2)$$

Where $A(f)$ is the Fourier transform of the coefficients, let $\bar{A}(f)=[\bar{a}_1(f)\bar{a}_2(f)...\bar{a}_m(f)]$ and $\bar{a}_{ij}(f)$ is the i, j^{th} element of $\bar{A}(f)$. Several estimators have been proposed to analyze connectivity between signals using the MAR coefficients. The most popular methods are:

1. Granger causality index (GCI)

A time domain method proposed by Hesse et al. [9] and defined as

$$GCI_{ij}(t)=\ln\left(\frac{VAR(\varepsilon_{i,n-1}(t))}{VAR(\varepsilon_{i,n}(t))}\right) \quad (3)$$

where VAR is the variance.

2. Partial directed coherence (PDC)

As a parametric approach in the frequency domain, PDC was introduced to detect causal relationships between processes in multivariate dynamic systems. PDC accounts for the entire multivariate system and makes differentiation between direct and indirect possible influences. It was initially proposed by Baccala et al. [7] and defined as

$$PDC_{ij}(f)=\frac{\bar{a}_{ij}(f)}{\sqrt{\bar{a}_j^h(f)\bar{a}_i(f)}} \quad (4)$$

The PDC from j to i represents the relative coupling strength of the interaction of a given source, signal j, with regard to some signal i, as compared to all of j's connections to other signals. Thus, PDC ranks the relative strength of interaction with respect to a given signal source while fulfilling the following conditions:

$$0\leq\left|PDC_{ij}(f)\right|^2\leq 1 \text{ and } \sum_{i=1}^{m}\left|PDC_{ij}(f)\right|^2=1 \quad (5)$$

For $i=j$, the PDC represents how much of X_i's own past is not explained by other signals.

3. Directed transfer function (DTF)

The DTF is a frequency-domain analysis technique to detect directions of interactions and it was proposed by Kaminski et al. [10]

$$DTF_{ij}(f)=\frac{H_{ij}(f)}{\sqrt{h_i^H(f)h_i(f)}} \quad (6)$$

We can observe that DTF uses the elements of the transfer function matrix H while PDC uses those of $\bar{A}(f)$. Since the computation of PDC does not involve any matrix inversion, it is computationally more efficient and more robust than DTF. Further, PDC is normalized with respect to the total inflow of information, but DTF is normalized with respect to the total outflow of information.

B. W-MVAR

The MVAR supposes that signals are stationary which is not realistic in the majority of biosignals and in particular in dealing with EHG. Here we propose a segmentation based approach to take into account the non-stationarity of the signals. In this case, the data is divided into short overlapping segments and the AR parameters are estimated from each segment. The result is a time-course of the AR parameters that describes the time-varying characteristics of the process. The segment length determines the accuracy of the estimated parameters and defines the resolution in time. A balance has to be maintained between time resolution (limited by stationarity) and the statistical properties of the fitted model. As a rule of thumb, the window length should possess a few times more data points than the number of estimated model parameters. Here, we choose the window length as 6s with overlap of 50% and data length (synthetic and real) equal to 100s, which we consider to be a good compromise between noise reduction and temporal resolution.

C. Signals

1. Synthetic signals

The main characteristic we want to test for here is the sensitivity of the methods to the non-stationarity of the signals. We generated a simulated process that contains linear non-stationary (LNS) relationships between the signals. We use a modified version of three dimensional VAR processes [8, 11] with time-varying parameters:

$$\begin{aligned} x_1(t) &= 0.5x_1(t-1) + 0.7x_1(t-2) + y(t)x_2(t-1) + \\ &\quad y(t)x_3(t-1)+\varepsilon_1(t) \\ x_2(t) &= 0.7x_2(t-1)-0.5x_2(t-2)+0.2x_1(t-1)+ \\ &\quad z(t)x_3(t-1)+\varepsilon_2(t) \\ x_3(t) &= 0.8x_1(t-1) + \varepsilon_3(t) \end{aligned} \quad (7)$$

with

$$y(t) = \begin{Bmatrix} 0.4 \text{ if } t\leq 7000 \\ 0 \quad \text{else} \end{Bmatrix} \quad (8)$$

which represent the influence from x_2 to x_1 and x_3 to x_1 and

$$z(t) = \begin{cases} 0.5\frac{t}{5000} & if \;\; t \leq 5000 \\ 0.5\frac{10000\text{-}t}{5000} & else \end{cases} \qquad (9)$$

representing the unidirectional influence from x_3 to x_2.

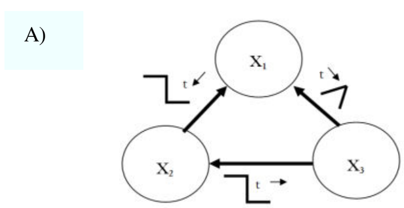
2. *Real signals*

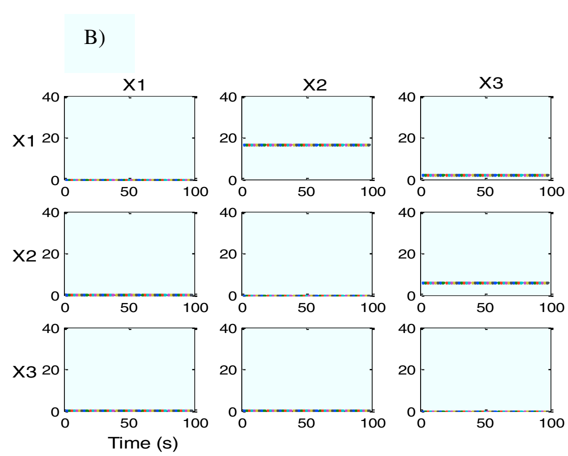
We used real uterine signals from 7 women during pregnancy and 6 women during labor. The signals were recorded by using 4x4 matrix posed on the woman abdomen. The measurements were performed at the Landspitali University hospital in Iceland, following a protocol approved by the relevant ethical committee (VSN 02-0006-V2). The sampling rate was 200 Hz. The EHG signals were segmented manually to extract segments containing uterine activity bursts. Bipolar signals are used here with 30 pregnancy bursts and 30 labor bursts. The 12 bipolar channels obtained by subtracting the signals pairwise up and down are used in the following analysis.

III. RESULTS

A. *Synthetic signals:*

In this section we present the results of applying GCI on the LNS system described above and the coefficients are estimated using the MVAR and the W-MVAR. The LNS system is described in Fig. 1A. A rectangular connectivity pattern is simulated between signal $x_2 \rightarrow x_1$ and $x_3 \rightarrow x_1$ and a triangular connectivity pattern is simulated between $x_3 \rightarrow x_1$.





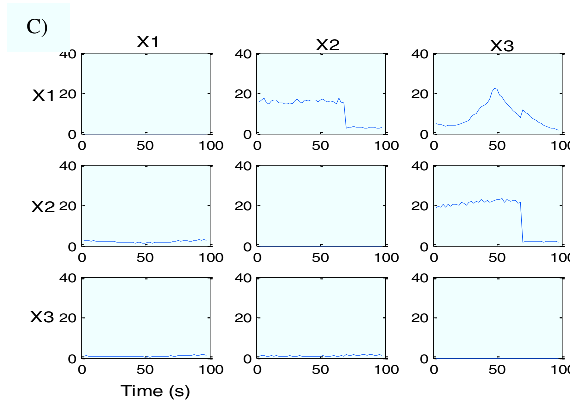


Figure 1. A) Simulated model B and C) GCI results using MVAR and W-MVAR respectively.

Fig. 1 (B and C) shows the results obtained. The figure indicates no change in the estimator values along all the signals which mean that MVAR cannot detect the relationships between the signals when a non-stationary characteristic is presented, while the connectivities are well detected by the W-MVAR model.

B. *Real signals*

The first and very important step is the choice of the model order. Several methods have been proposed to estimate the optimal order of MVAR model. In this work we use the Schwarz Bayesian Criterion (SBC) [12]. The model order computed by SBC of the real signals was about 35. We found the same value when using another order estimation criterion namely the Final Prediction Error (FPE).

On the real signals we are more interested in the frequency-based methods such as DTF and PDC. A comparison (not shown) between the two methods PDC and DFT indicates the superiority of PDC to detect the connectivity between synthetic signals. These observations confirm the results of Baccala et al. [7] which indicated that PDC is more powerful than DTF in analyzing signal relationships tested on several synthetic simulations and EEG real signals. For this reason, we applied the PDC method to the EHG signals as the main aim is to find a tool that can differentiate between signals for women during normal pregnancy and signals from women in labor.

The quantitative criterion estimated from PDC is obtained as follows:

- Compute evolution of PDC between the 12 bipolar EHG signals to obtain 12x12 matrices for each contraction.
- Compute the maximum of PDC values.

The mean value over the matrix is the quantitative value representing each contraction used in the classification procedure.

We computed this criterion by estimating the coefficients using both MVAR and W-MVAR. Table 1 illustrates the classification results of pregnancy and labor bursts by both methods. The results indicate mean and standard deviation of

PDC values, it shows that MVAR shows poor performances in distinguishing labor and non-labor bursts with $p=0.12$, while the signals are very well classified by the W-MVAR with $p<0.01$. We note that the pregnancy values are similar with MVAR and W-MVAR, while the difference is clear in the labor bursts. This seems to indicate that labor signals have more pronounced non-stationary characteristics than the pregnancy signals which are taken into account by the W-MVAR.

TABLE I. COMPARAISON BETWEEN MVAR AND W-MVAR IN CLASSIFYING PREGNANCY AND LABOR BURSTS

	MVAR	W-MVAR
Pregnancy	0.045±0.03	0.05±0.045
Labor	0.067±0.04	0.12±0.07
P *(two tailed student test)*	0.12	<0.01

IV. DISCUSSION

In this paper we have proposed a time varying version of the multivariate autoregressive model to investigate the connectivity between non-stationary signals. The proposed model was tested on synthetic signals as well as real signals. On the synthetic signals, W-MVAR showed a clear superiority in detecting relationships between signals when non-stationary characteristics are present in the signals.

The application of the MVAR and W-MVAR on EHG signals showed clearly that W-MVAR is very good in differentiating pregnancy and labor signals whereas MVAR is not. The successful estimation of PDC depends however on the reliability of the fitted MVAR model, since all of the necessary information is derived from the estimated model parameters. The directionality aspect could be investigated also by using the monopolar signals denoised recently by the algorithm called CCA_EMD [13]

The window length is an important issue because it determines the resolution in the time- and frequency domain. Here, window length for W-MVAR was chosen empirically and as appropriate for the EHG signals. We think that additional work is needed to define an automatic criterion for the optimal window length to make the application more general and useful for other biomedical signals, as well as comparison with other existing methods.

V. CONCLUSION

In this paper, we proposed a time varying version of MVAR model. The proposed version was shown a better performance than classical stationary MVAR on synthetic signals as well on real EHG signals. The use of W-MVAR indicated a high capacity to differentiate non-labor and labor signals. We think that W-MVAR could be a powerful tool to the classification of pregnancy and labor signals for labor detection and then preterm labor prediction.

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