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From Electrohysterogram Preview by a Deep Learning Method to Labor Prediction in Pregnant Women

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Abstract

The Electrohysterogram (EHG) is recognized as one of the best signatures of uterine contractions during gestation which has been used in the literature for the prediction of preterm births. The N-BEATS deep learning method has been applied to a dataset from an example of EHG by considering their first six principal components. Thus, it can be seen that the preview of EHG, and the early prediction of labor from the N-BEATS method, depends on the data size and recordings' duration.

Keywords: Principal component; Uterine contraction; Machine learning; Prediction

Introduction

Maternal and child health is and remains a public health issue. But the approaches vary between low and high income countries. What is common to both is the problem of preterm births (gestation week less than 37 weeks and more than 26 weeks), which still remains a huge public health issue. In addition to this, for low-income countries carrying a pregnancy to term (gestation week over 37 weeks) is still a public health issue; whereas this is no longer the case in high-income countries. This is due to the lack of sufficient and quality health structures, adequate technical facilities and available qualified human resources. The problem is even more acute in rural and peri-urban areas. In this context, in order to solve the problem of premature births, high-income countries have initiated research that has led to the recognition of the Electrohysterogram as an effective technique for monitoring pregnancies in pregnant women. Several methods have been developed around it and several parameters have been discovered for its characterization in order to diagnose preterm birth earlier. In the literature, thirty of these parameters have been found to be the most widely used.

In order to address the various deficits mentioned above for low-income countries, we are interested in the prediction of labor in pregnant women with full-term pregnancies. It is in this context that we have sought to better understand the techniques of external recording of EHG and especially electrodes positioning on the pregnant woman's abdomen [1]. In the same vein, we wanted to be able to distinguish between physiological contractions related to pregnancy and those leading to labor; the methods for doing so were identified in the literature [2]. As a logical extension of this, in this work we are interested in predicting labor by forecasting the behavior of the EHG signal using a deep learning method. We will start with the principal component analysis, which will allow us to make an objective choice of the main components to be considered in the dataset to be provided to the learning algorithm. In the following sections of this paper we will describe the different methods used, the results obtained after their application, the discussion of these results and the conclusion.

Method

Used data

The Term-Preterm EHG database [3] was used in this work. In our study, we considered the record with the identity 1737 and carried out at 35.6 weeks of gestation with delivery at 39 weeks (full term pregnancy). Then, as data used in this study, we exploited the thirty (30) parameters most used in the literature for the characterization of the EHG signal and uterine contractions (Table 1).

Empirical mode decomposition

The raw data from PhysioBank was then subjected to Empirical Mode Decomposition (EMD).

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This is a method used to analyze and decompose non-stationary and non-linear signals. It performs operations that partition a series into *N* finite "modes" (IMFs: Intrinsic Mode Functions) without leaving the time domain [4]. The first extracted IMF contains the fastest oscillations of the signal, the last extracted IMF concerns the slowest ones, while the residual, r(t), represents the signal trend [5,6].

$$EHG(t) = \sum_{i=1}^{N} IMF(t) + r(t)$$

The usefulness of EMD in our work is that it allows us to eliminate unnecessary variations in the original signal.

Principal component analysis

This is a widely used dimension reduction technique. Given a dataset with *n* features, the objective is to have *k* features with $k \leq n$ so that the *k* features retain most of the variation present in all the original variables. Let us assume the following dataset in matrix form to illustrate the technique:

$$data = \begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ a_3 & b_3 & c_3 \end{bmatrix} \quad (1)$$

with each row representing an observation and each column a parameter.

By associating to each dataset a_i, b_i, c_i a function f_i, the average of each column gives:

$$\hat{f}_1 = \frac{1}{N}\sum_{i=1}^{N} f_i \ ,$$

which allows us to obtain the covariance of each parameter f_i through:

$$\mathrm{cov}(X,Y) = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \hat{x})(Y_i - \hat{y}) \quad (2)$$

Thus, following the rules of covariance we have:

$$\mathrm{cov}_{data} = \begin{bmatrix} \mathrm{cov}(f_1, f_1) & \mathrm{cov}(f_1, f_2) & \mathrm{cov}(f_1, f_3) \\ \mathrm{cov}(f_1, f_2) & \mathrm{cov}(f_2, f_2) & \mathrm{cov}(f_2, f_3) \\ \mathrm{cov}(f_1, f_3) & \mathrm{cov}(f_2, f_3) & \mathrm{cov}(f_3, f_3) \end{bmatrix} \quad (3)$$

Considering the square matrix $A \in \mathbb{R}^{n\times n}$ and $\lambda \in \mathbb{R}$ an eigenvalue of *A*, $x \in \mathbb{R}^n - \{0\}$ is the corresponding eigenvector of *A* if:

$A_x = \lambda_x$ (eigenvalue equation)

Thus the eigenvalues of *A* are roots of the characteristic equation:

$$det(A\text{-}\lambda I) = 0 \quad (4)$$

If *I* is the identity matrix corresponding to *A*, we have:

$$\det(A-\lambda I) = \det\left(\begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ a_3 & b_3 & c_3 \end{bmatrix} - \lambda\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}\right) = \det\left(\begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ a_3 & b_3 & c_3 \end{bmatrix} - \begin{bmatrix} \lambda & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{bmatrix}\right) \quad (5)$$

$$\det(A-\lambda I) = \begin{vmatrix} a_1-\lambda & b_1 & c_1 \\ a_2 & b_2-\lambda & c_2 \\ a_3 & b_3 & c_3-\lambda \end{vmatrix} \quad (6)$$

Solving this equation (using the Sarrus rule), we have an equation of the form: $a\lambda^3 + b\lambda^2 + c\lambda + d = 0$.

After solving this equation we obtain the eigenvalues: λ_1, λ_2, λ_3, with:

$$\lambda_1 > \lambda_2 > \lambda_3 \quad (a)$$

We then obtain, by solving the eigenvalue equation, the different eigenvectors:

$$v_1 = \begin{bmatrix} v_{11} \\ v_{12} \\ v_{13} \end{bmatrix},\ v_2 = \begin{bmatrix} v_{21} \\ v_{22} \\ v_{23} \end{bmatrix},\ v_3 = \begin{bmatrix} v_{31} \\ v_{32} \\ v_{33} \end{bmatrix}$$

v_1, v_2, v_3, represents respectively the eigenvectors of λ_1, λ_2, λ_3.

Considering (a), we can choose $k \leq n$ principal components with *k*=2 in our case. This giving us the corresponding matrix:

$$W = \begin{bmatrix} v_{11} & v_{21} \\ v_{12} & v_{22} \\ v_{13} & v_{23} \end{bmatrix} \quad (7)$$

This can still be written by transformation into a new subspace in the form:

$$y = W^T \times data^T \quad (8)$$

It is therefore a technique whose objectives are to: Simplify and reduce data, select variables, classify, model, predict, etc. [7]. It also allows us to identify patterns in the data, and to compress them by reducing the higher dimensions to the lower ones, without causing any effect on the whole data or without losing important information [8]. In other words, at the end of this analysis, we obtain a given number of Principal Components (PCs) such that this number is less than or equal to the number of initial dimensions of the dataset.

Stationarity and deep learning

The stationarity of the data series to be sent to the forecasting algorithm must be ensured. For this purpose, the method of visual observation of the signal, its mean and its standard deviation, all represented on the same graph, is used. A statistical method is associated with this for increasingly complex data series. In our case, the Augmented Dickey Fuller test [9] was used as it is the most widely used statistical method of stationarity analysis in the literature. It is a mathematical method based on a null hypothesis and an alternative. The non-stationarity of the data is often considered as a null hypothesis. The objective is to eliminate it by obtaining a p-value lower than 0.05.

Once the stationarity of the data series is ensured, the forecasting process can start. For this purpose, the deep learning method N-BEATS [10] has been identified. It is a predictive algorithm with a deep neural architecture based on backward and forward residual links and a very deep stack of fully connected layers. The architecture has a number of desirable properties, being interpretable, applicable without modification to a wide range of target domains, and fast to train [10]. It is a method that has proven itself in the field of time series forecasting in recent years. For its implementation, *PyTorch Forecasting* was used, itself being a PyTorch-based package with an open source machine learning framework (Figure 1).

Results

The application of the EMD on the EHG signal of our example (woman at 35 weeks of gestation) over a period of 20s centered on the peak characterizing the uterine contraction (Figure 2), gives 4 IMFs among which we selected the second one in the framework of our study. The choice to focus on the periods of contraction is the one most often made in the literature.

After obtaining the IMFs from the EMD, when we apply the principal component analysis considering the 30 parameters, we obtain Table 2. Considering the results in Table 2, we have identified the 15 best parameters (RMS, MF, TM5, SM3, MYOP, ApEn, Tr, MAV2, TM3, SE (SampEn), VCF, MNF, LOG, ZC, MAV1) by taking in order the principal components and the parameters representing them.

At the end of this, we notice that the first six principal components

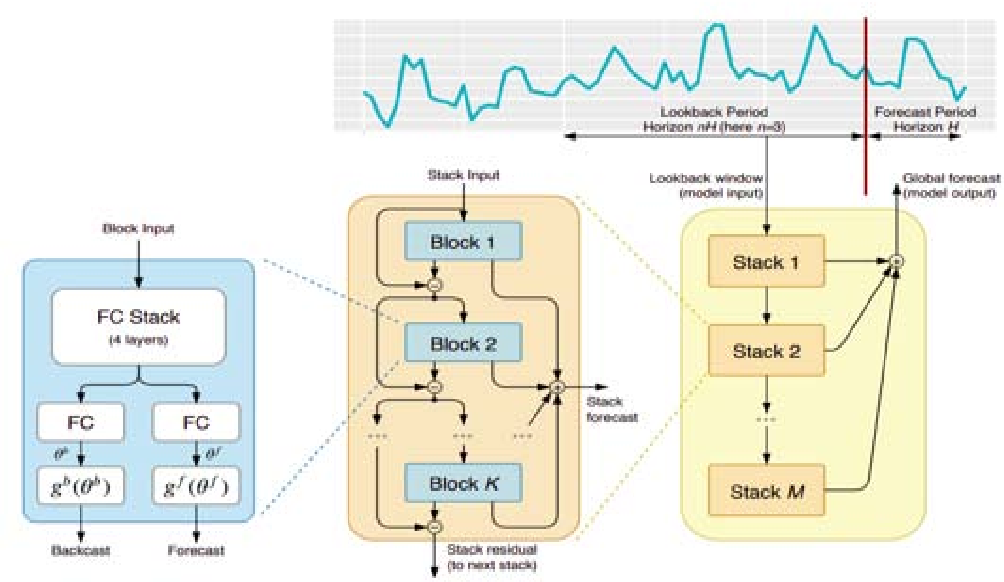

Figure 1: N-BEATS architecture.

Table 1: Summary of the most used parameters in the literature.

Authors	Title	Parameters/features
Garcia-Gonzales et al., 2013	Characterization of EHG contractions at term labor by nonlinear analysis	**Nonlinear**: Sample Entropy (SampEn)
Alamedine et al., 2013a	Parameters extraction and monitoring in uterine EMG signals. Detection of preterm deliveries	**Linear**: wavelets variation (W1, W2, W3, W4, W5), deciles (D1, D2, D3, D4, D5, D6, D7, D8, D9), Mean Frequency (MNF), Peak Frequency (PF), relative energy
Alamedine et al., 2013b	Comparison of different EHG feature selection methods for the detection of preterm labor	Linear: MNF, PF, Déciles (D1….D9), (W1….W5)
		Nonlinear: Time reversibility (Tr), Lyapunov exponent (Ly), SampEn, Variance Entropy (VarEn)
Shulgin and Shepel, 2014	Electrohysterographic signals processing for uterine activity detection and characterization	**Linear**: Root Mean Square (RMS)
		Nonlinear: p(n, f), f1(n), Ex(n), psi(n)
Liu et al., 2017	Comparison of electrohysterogram characteristics during uterine contraction and non-contraction during labor	**Linear** : RMS, PF, Median Frequency (MF), MNF, (W4, W5)
		Nonlinear: Tr
Hao et al., 2019	Application of decision tree in determining the importance of surface electrohysterography signal characteristics for recognizing uterine contractions	**Linear**: RMS, Standard Deviation (STD), Log detector (LOG), Mean Absolute Value (MAV), Simple Square Integral (SI), Differente Absolute Standard Deviation Value (DAS), Average Amplitude Change (AAC), variance (VAR), MF, PF, Puissance
		Nonlinear: TR, Ly, SampEn

alone constitute 90% of the total information on the signal from the characterization point of view. Thus, in the following, these six principal components will be used to train our deep learning and decision algorithm for predicting the future behavior of our EHG signal. The application of our deep learning method to our dataset leads to Figure 3.

As we can see from the different graphs, the higher the number of epochs, the less the model learns. The number of cycles refers to learning across the entire training data set. In this case, we will opt for small training cycles.

Discussion

In the literature, a fixed number of parameters have often been used regardless of the patient; in our work the parameters are selected according to the EHG signal, the characteristics of which depend on the patient, the week of gestation, and external factors that also affect the uterine contraction muscles. Indeed, when applying the method to other examples, the parameters do not appear in the same order from one woman to another and from one week of gestation to another. Furthermore, we find that it is unnecessary to go beyond a certain number of principal components (usually 6). Since often the first six principal components already represent 90% of the signal information if not more. We therefore recommend the analysis of the principal component before any characterization of the EHG

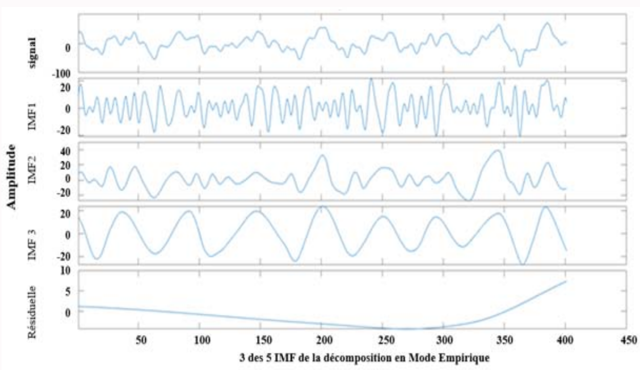

Figure 2: EMD over a period of 20s from a woman at 35 weeks of gestation.

Table 2: Principal components of a patient at 35 weeks of gestation.

PC	Parameters	PC	Parameters	PC	Parameters
PC1	RMS	PC11	SampEn	PC21	TM4
PC2	MF	PC12	MAV2	PC22	IEMG
PC3	TM5	PC13	MF	PC23	RMS
PC4	SM3	PC14	VCF	PC24	SM1
PC5	MYOP	PC15	MNF	PC25	WL
PC6	ApEn	PC16	LOG	PC26	IEMG
PC7	Tr	PC17	ZC	PC27	TTP
PC8	ApEn	PC18	RMS	PC28	MNP
PC9	MAV2	PC19	MAV1	PC29	SSI
PC10	TM3	PC20	DASDV	PC30	WAMP

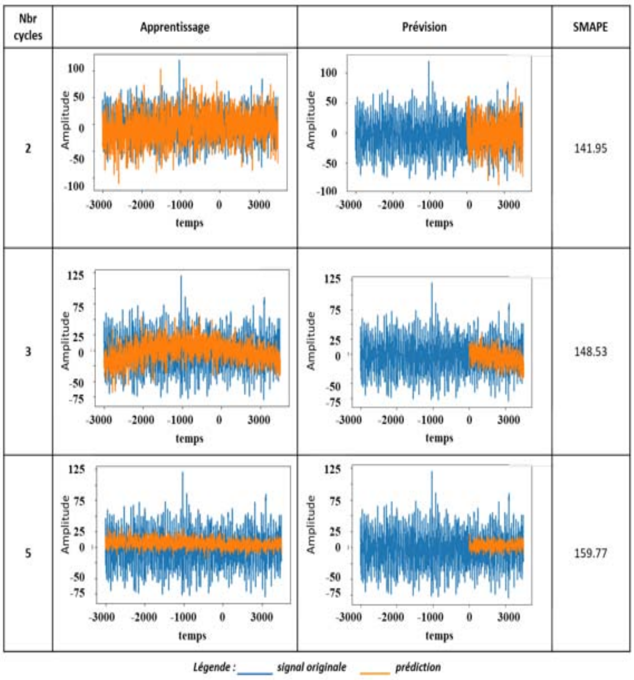

Figure 3: Summary of learning and forecasting by cycle.

signal and thus of the uterine contractions. So, parameters that do not actually represent a good proportion of the signal information can be discarded, unless one wants to study the signal specifically with respect to these parameters.

In our work, due to the sampling frequency and time interval, we have made forecasts over short periods. This can be remedied by increasing for example the recording time to extend the prediction over an earlier prediction horizon. The physiological signals' forecasting and in particular the EHG ones, is still at an immature stage, with few articles on this subject. In our perspectives, we would like to build up larger datasets with longer recording times in order to make predictions over hours.

It should also be noted that in this work we have not stuck to the standard classification on the basis of parameters or their associated methods. This is generally done in the literature so far to see which parameter(s) better identify or predict the contractions that will lead to labor, or which method(s) achieve this result or the classification between preterm and term birth. Future perspectives would be to consider representative parameters of the principal components for prediction (corresponding to what is done in the literature) and to compare the results with those obtained by proceeding in the way indicated in the present work. But the major limitation of our work is the size of our data due to the lack of a more representative database of local populations and more adapted to our needs. We hope to overcome this limitation with the validation of our recording kit.

Conclusion

In this work, we have prioritized the most commonly used parameters in the literature by the proportion of information on the signal they represent, using the principal component analysis method. This allows us to avoid choosing the parameters for characterizing the EHG at random; especially as the order of the main components of the EHG as observed here varies from one patient to another and according to the weeks of recording. Furthermore, this allows us to know that the parameters we consider in our prediction models best represent the signal. Our prediction model here is based on predicting the behavior of the EHG signal by the deep learning method called N-BEATS. This is a recent method that is proving itself in other areas compared to existing methods. It allows a learning process which, in order to last in time, needs a large quantity of data at the beginning, which was not possible in our case due to the limits of the exploited database. It would therefore be desirable to have a database of its own for longer predictions.

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