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Evaluation of Different Feature Uterine Electrohysterography (EHG) Signals

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ABSTRACT

In this paper, One of the remaining challenges for the scientific-technical community is predicting preterm births, for which electrohysterography (EHG) has emerged as a highly sensitive prediction technique. Sample and fuzzy entropy have been used to characterize EHG signals, although they require optimizing many internal parameters. Both bubble entropy, which only requires one internal parameter, and dispersion entropy, which can detect any changes in frequency and amplitude, havebeen proposed to characterize biomedical signals. In this work, we attempted to determine the clinical value of these entropy measures for predicting preterm birth by analyzing their capacity as an individual feature and their complementarity to other EHG characteristics by developing six prediction models using obstetrical data, linear and non-linear EHG features, and SVM to select the features. Both dispersion and entropy better discriminated between the preterm and term groups than sample, spectral, and to linear features, and indeed, the improvement in model performance by including other non-linear features was negligible. The best model performance obtained an F1-score of 90.1 ± 2% for testing the dataset. hereby contributing to the transferability of the EHG technique to clinical practice..

KEYWORDS

EHG, Labor, Statistical and non-linear features,.

1 Introduction

Survivors of preterm birth suffer with neuro-developmental or behavioural defects, including cerebral palsy, and motor and cognitive impairment. In addition, preterm births also have a detrimental effect on families, the economy, and society as a whole. In 2009, the overall cost to the public sector, in England and Wales, was estimated to be nearly £2.95 while in 1994, in the United States alone, it was estimated that, of the $820 million spent on hospitalising women with suspected preterm labour, $360 million was for women who did not actually deliver during their stay. As well as patients being incorrectly diagnosed with preterm labour (false positive results), 20% of patients displaying symptoms or preterm labour were given false negative results: they were denied early admittance, but eventually went on to deliver prematurely. In 2001, the cost of care increased rapidly. According to a nationwide survey carried out by hospital costs for preterm infants in the United States was $12.4 billion.

Treatment Strategies

Developing a better understanding of preterm deliveries can help to create preventative strategies and thus positively mitigate, or even eradicate, the effects that preterm deliveries have on babies, families and healthcare services. As well as investigating preterm deliveries, several studies have explored preterm labour (the stage that directly precedes the delivery). In spite of these studies, there is no internationally agreed definition for preterm labour.

Nonetheless, in practice, women who experience regular contractions, increased vaginal discharge, pelvic pressure and lower backache tend to show Threatening Preterm Labour (TPL). While this is a good measure, , suggest that clinical methods for diagnosing preterm labour are insufficient

One possible approach to mitigate many of these concerns is to utilise advances made within the machine learning community. This present approach examines the use of Electrohysterography (EHG) signals, feature engineering and machine learning algorithms to classifying term and preterm births. This has been achieved by
1) filtering the raw EHG signals to remove unwanted artefacts,
2) generating features from EHG records to classify preterm and term delivery records,
3) use different sized training sets to test the effect that these proportions have on the results,
4) and use dataset resampling strategies to balance the data.
The aim is to providing a viable solution that addresses this global health problem by managing the human gestation period better to improve health and reduce costs.

2. Literature Review

Ye-Lin et al. (2014), extracted 11 features from EHG signals. These properties are spectral, temporal, and nonlinear. They investigated the classification performance with these 11 extracted features. 2-fold cross-validation, repeated 50 times, was applied across 3 classifiers, including Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and SVM with RBF kernel function. As a result of the study, the QDA classifier gave the best classification performance with 92.2% success. Ahmed et al. (2017), determined that the multivariate multiscale fuzzy entropy (MMFE) algorithm is superior to the multivariate multiscale entropy (MMSE) in both synthetic and real EHG signals. Chen and Hao (2017), presented a new method for feature extraction and classification of EHG signals based on Hilbert-Huang transform (HHT) and extreme learning machine (ELM).
The study of Idowu (2017), included the records of 262 women who gave birth in the normal period and 38 women who gave birth prematurely. Innovative signal processing techniques and the application of machine learning algorithms in the analysis of EHG signals are important in estimating the risk of preterm birth. In his study, Levenberg-Marquardt trained Feed Forward Neural Network, Radial Basic Function Neural Network, and Random Neural Network classifiers were used. As a result, 91% sensitivity and 84% specificity values were obtained. The average error rate is 12%. Acharya et al. (2017), made a new proposal for automatic prediction of pregnant women who will give birth prematurely by using EHG signals. Eight different features were extracted in the study. These extracted features were analyzed with the vector machine (SVM) classifier for automatic differentiation and as a result, 96.25%, 95.08% sensitivity, and 97.33% specificity were obtained.
Muszynski (2019), examined the estimation of the risk of preterm birth by analyzing electrical parameters from EHG. The results obtained make it possible to improve the estimation of the risk of preterm birth relative to routinely used instruments. Degbedzui and Yüksel (2020), proposed a new method for diagnosing preterm labor without treatment based on the classification of Electrohysterography (EHG) signals. By constructing elements of a feature vector representing the time-varying spectral content of the EHG signal, the centroid frequencies of the frames were calculated. It has been shown that the proposed approach outperforms other methods and can be used effectively in the classification of EHG signals for term-preterm diagnosis.
Zardoshti et al. (Zardoshti Wheeler 1993) evaluated a number of features commonly used when dealing with EHG signals. These included integrated absolute value, zero crossings and auto-regression coefficient. However, despite their good discriminant capabilities, a precise frequency threshold for accurate contraction and delivery classification, over different patients, could not be determined. Fergus et al. (Fergus et al. 2013), conducted a broad study of techniques for analysing the features of the EHG signal where, features such as peak frequency, median frequency, root mean square and sample entropy, performed particularly well when discriminating between term and preterm records, with several of the classification models used to validate the approach reporting very good results

3. Methodology

In order to conduct our experiments using the TPEHG dataset, the proposed methodological framework is presented in Figure 4.2. These phases consist of raw EHG signals (data collection), signal pre-processing, feature extraction, oversampling with the support vector machine(SVM) generating test and training models, feature selection, classification, combining classifiers, validation, and the presentation of results. The remainder of the chapter will provide a more in-depth discussion of each of these processes within the proposed methodological framework.

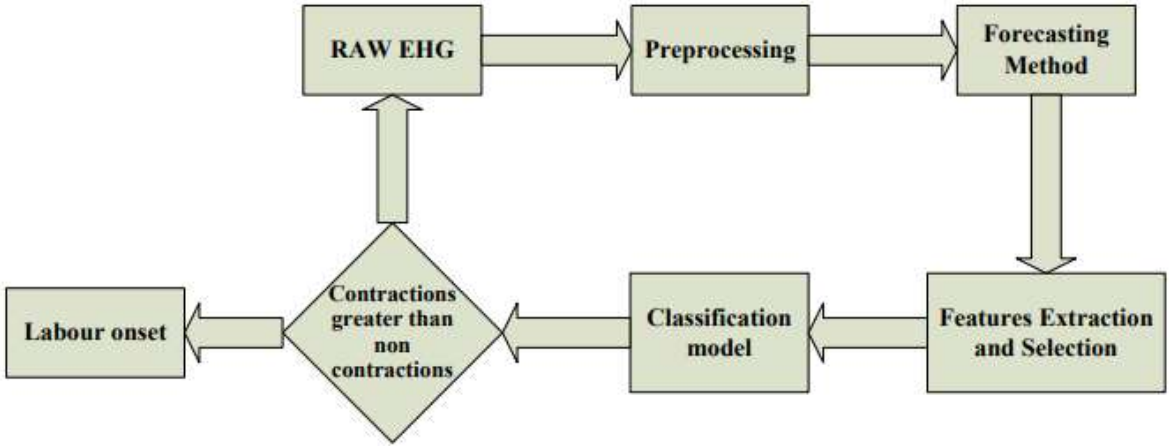

Figure 1: Methodology Phases

Features are values which, optimally, accentuate relevant characteristics of a signal. Hence, feature extraction is the procedure of deriving characteristics from the signals to create a better representation of their similarities and dissimilarities. describes features as computed values that should be representative of the signal and reproducible at different times. It describes as important criteria:
• lower dimension than signal
• high inter-class variance and low intra-class variance
• provide a robust and enhanced representation of the signal
Regarding the context of EHG recordings study, one important detail is whether contraction segments were used or the whole record. This choice will have an influence on features selection, as the relevant characteristics to profile a single contraction may differ from those that attempt to make sense of a whole record.
A concerning problem with directly studying the contraction segments is the non-linear characteristics of the uterine physiological events. These may imply better results from non-linear features over linear ones, as a way to represent this complex, non-linear system. states non-linear techniques are less accurate when considering shorter amount of data, which becomes a problem given the time contractions take
Nevertheless, the use of contraction segments allows other considerations such as standard time-domain descriptions of contractions and one can hypothesize that it provides more specific information over relevant events.

Linear Time Domain Features

The most studied topic over EHG records is the prediction of preterm labor, for which the data is analyzed to identify patterns that differentiate preterm EHG records from normal pregnancies. Studies on preterm pregnancy may also try to find the same differentiation over labor records in comparison to those of pregnancy. In this regard, the selected features should outline a state of labor proximity.
The first group of features that will be examined are linear, time-domain features.
These are listed in Table 4.1, with fields:
• Feature: Refers to the name of the feature;
• Context: Refers to the data used, more specifically, ’EHG signal’ refers to a study where the whole record was used, while the abbreviation ’EHG segm.’ refers to a
study where the signal was segmented;
• Description: Attempts to describe the significance of the feature and provide studies
comments on their results.

Feature Extraction from EHG Signals

Feature extraction transforms raw signals into more informative signatures that can assist in grouping different classes. In other words, features are synonymous of input variables or the attributes of a dataset that provide a good representation of a specific domain, related to the available measurement. In this thesis, several feature extraction techniques have been utilized. These are applied to the channel 3 records using the filter parameters previously discussed. Table 2, provides a summary of the mathematical proofs for each of the features use

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4. Result

,ten features were extracted from channel 8 signals in the TPEHG database. This has never been done in this area of research. The rational of this approach is to look at linear and nonlinear feature methods that could increase the prediction rates in our chosen classifiers. Our results show that apart from features like mean frequency, peak frequency and sample entropy features like standard deviation , maximum, minimum, cepstrum can also help algorithms to learn better. While these features have typically be used in EMG they have r been used to monitor electrical activity in the uterus

Table 1 Feature Difference between Term & Preterm

Feature	Term	Preterm
entropy	-0.84384	-0.85226
rms	0.000579	0.002215
mean	-1.60E-05	-4.89E-05
max	0.001613	0.005702
min	-0.00155	-0.00768
cepstrum	-0.02873	-0.02313
variance	3.37E-07	4.93E-06
Std dev	0.000581	0.00222
ppsd	2.60E-06	5.90E-05
Peak freq	0.6	0.3

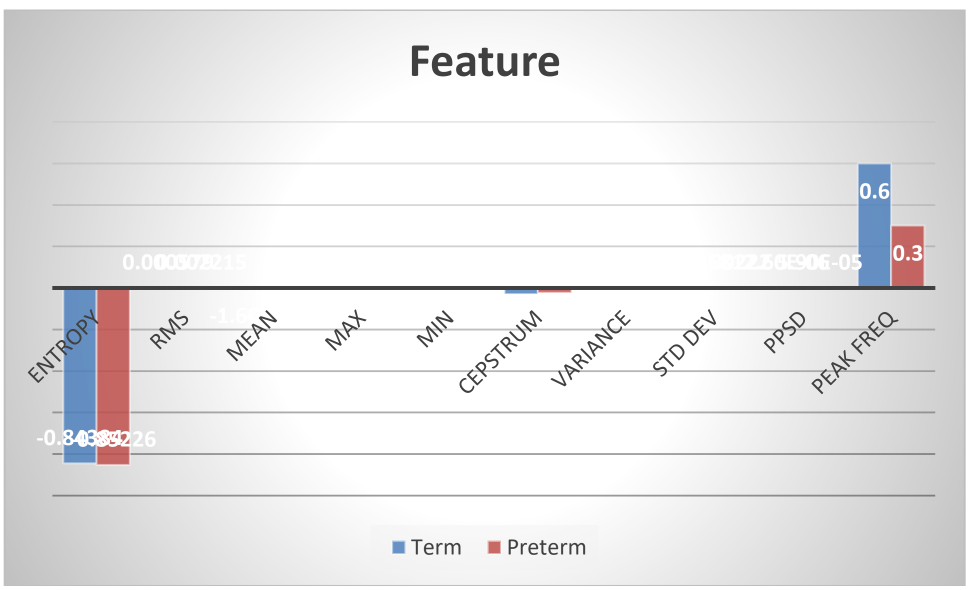

Figure 2: Comparative graph of Term & Preterm Signal

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