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Bio-Magneto Sensing and Unsupervised Deep Multiresolution Analysis for Labor Predictions in Term and Preterm Pregnancies †

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Abstract: The effective prediction of preterm labor continues to be a topic of interest for research within pregnancy medicine, where uterine muscle contraction signals have shown to be insightful towards the inference of a potential preterm birth. Magnetomyography (MMG) is a physiological measurement-based tool which measures the orthogonal offset of bioelectrical manifestations from uterine contractions and may serve to predict potential premature delivery with enhanced accuracy. The decoding of the physiological signal is an area of substantial research where classical signal processing approaches and metaheuristics optimization routines have been utilized towards the postprocessing and decomposition of the MMG signals. This work requires a degree of expert knowledge and an understanding of tuning and parameter initialization. As part of strides towards creating a more automated clinical decision support platform for the predictions of preterm labor, we employ the use of the deep wavelet scattering (DWS) model. This methodology allows for a deep multiresolution analysis alongside unsupervised feature learning, for the postprocessing of candidate MMG signals. The DWS is combined with select pattern recognition-based prediction machines in order to assemble a clinical decision pipeline for prediction of the states of various pregnancies, with a greater degree of machine intelligence. The patient cohort consisted of a multi-ethnic demographic population comprised of preterm and term pregnancies, where birth occured both under and over 48 h of labor commencing. Contrasting results were found between the various methods utilized from the literature and the DWS, using the logistic regression algorithm. It was seen that the DWS produced a slightly lower accuracy in comparison, as a trade-off for its streamlined unsupervised feature extraction prowess. Further work would now involve the application of various other machine learning methods in an attempt to assess and identify the most appropriate machine learning method with the DWS that proves to be the most accurate.

Keywords: keyword1; keyword2; keyword3; (List three to ten pertinent keywords specific to the article yet reasonably common within the subject discipline.)

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1. Introduction

Labor is the culmination of pregnancy involving the safe delivery of a fetus from the womb of a female, where different timespans of birth, including preterm birth, can occur during this process, [1–3]. It is important to be able to identify potential preterm births in order to be able to commence proactive care strategies where necessary [1]. The medical literature and earlier research have shown that uterine contraction signals contain an encoding which can be utilized towards an analytical forecast of a potential labor prediction and an inference for a preterm birth [1]. As the uterine wall itself is a muscle, its involuntary contractions take place with ionic current flow, which are electrophysiological manifestations that can measured from either a bioelectric or biomagnetic perspective [4]. The affordability and relative ease of acquisition of measurements via electrohysterogram (EHG) means that the majority of recordings come from a bioelectric perspective [1]. However, the limitations of EHG are based around the attenuation of the bioelectrical signals as they steadily travel through tissue from source contractions to the receivers [1]. Regarding the orthogonal counterpart, the magnetic offset can be acquired with a magnetomyography (MMG) instrumentation which is robust from the issue of tissue conductivities [4].

Prior studies into the use of MMG for the prediction of labor imminency has been done by Eswaran et al. [5], who adopted the high resolution superconducting quantum interference device array for reproductive assessment (SQUID Array for Reproductive Assessment [SARA]), which comprises 151 MMG channels. The dataset from Eswaran et al.'s [5] work has been utilized by multiple authors for various depths of research relating to the topic, including by the author of this paper alongside various signal processing and machine learning models towards improved means of predicting an imminent labor case [6,7]. The majority of the analytics adopted involved the use of classical signal processing and multiresolution analysis, alongside various machine learning methods [7]. It should be noted that the adopted signal processing methods were stringent in their use of "handcrafted" features that relied on expert knowledge as part of their selection and extraction.

The emergence of deep learning has given rise to alternate means of feature extraction methods with the ability to extract deep multiscale features from a candidate signal without the need for any specific expert knowledge, in contrast to handcrafted features [8]. The deep wavelet scattering (DWS) comprises a merger between the convolutional neural networks (CNN) from the deep learning architecture, and the wavelet decomposition from the multiscale resolution aspect, which together allow multiresolution unsupervised feature extraction and characterization of a signal [8]. This recent approach has encountered an uprise in the literature, with applications spanning across various aspects of clinical medicine due to the appeal of having an automated and unsupervised feature extraction approach.

Thus, as part of this work, the authors aim to adopt the DWS method towards evaluating the extent to which it can differentiate between two sets of labor states based on the MMG dataset, whilst contrasting the performance with prior related literature.

2. Materials and Methods

2.1. Materials

The dataset used for this work comes from the publicly available Physionet database, which hosts data from a number of pregnant patients who delivered a mixture of both term and preterm neonates, whilst spanning a range of ethnicities, i.e., Caucasian, Black, and Hispanic. The data contains two class labels, which corresponds to those patients whose labour was completed within 48 h of the MMG acquisition measurements, and hose whose labours lasted over 48 h [9]. The data was initially acquired at an acquisition rate of 250 Hz, which was then subsequently downsampled to 32 Hz. An illustration of MMG data acquisition can be seen in Figure 1. A total of 22 patients' data were utilized for the work done as part of this study.

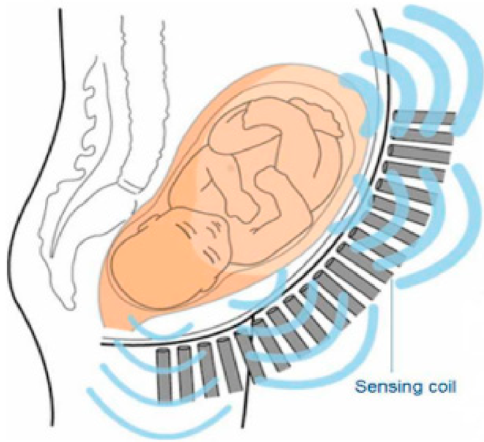

Figure 1. Illustration of MMG data acquisition [10].

A database containing further information on the data acquisition process, ethical approval and patient information consent, can be seen on the Physionet website [9].

2.2. Methods

2.2.1. DWS

The DWS is capable of extracting unsupervised features that are continuous and mostly robust to translations whilst comprising features of both the wavelet decomposition and the CNN [8]. For the DWS, the wavelets and filters are preset in order to reduce the overall computational complexity of the method; it also possesses the strength of being able to work with a constrained number of samples due to its multiscale principle and configuration [8]. A mathematical formalism of the DWS configuration can be seen in Andén and Mallat [8], where the computational interpretation of the DWS involves a deep CNN which is responsible for iterations, whilst convolving through the wavelets and nonlinear modules, alongside an average scaling function. For the implementation of the DWS, the Gabor wavelet was used as the mother wavelet, while the scale invariance of 1 s was used; the filter banks were set to 8 wavelets per octave in the first filter bank, followed by 1 wavelet per octave in the second filter bank.

2.2.2. Linear Series Decomposition Learner (LSDL)

In order to benchmark and contrast the performance of the DWS, results from the LSDL were also included from the literature. The LSDL is a metaheuristically driven method which is capable of separating a candidate signal into multiple components with a view towards finding an optimal region in a signal, which can minimize redundancies and maximize prediction accuracy [11–13]. Its algorithmic formulation is based around artificial intelligence-based metaheuristic reasoning, which guides towards the systematic separation of a signal using a designated basis function alongside an embedded cost function [11–14].

The inceptive study for the LSDL was based on a source separation exercise involving a heterogenous mixture of powders which produced highly variable nonlinear signals, for which the LSDL appeared adept at estimating, the results of which superseded the classical wavelet decomposition [11–14]. The LSDL has been adopted in a multitude of other studies for which there exist signals that exhibit similar dynamic behavior to its inception exercise, which has led to applications within clinical medicine in areas spanning obstetric medicine, oncological medicine, surgical anesthesia, rehabilitation, and psychiatry [15–18]. The preprocessing act of the LSDL has been seen to enhance the modelling prowess of the candidate signals in question [15–18].

2.2.3. Handcrafted Features and Machine Learning Models

As a means towards forming a contrastive basis to the results from the DWS, the following features were extracted: mean of peaks, waveform length, slope sign change, root mean squared, cepstrum, maximum fractal length, median frequency, simple square integral, variance, 4th order autoregressive coefficient, Higuchi fractal dimension, detrended fluctuation analysis, peak frequency, and sum of peaks [4].

The SMOTE synthetic sample generator was also utilized as a means towards class balancing purposes, in order to minimize the effect of decision bias on the classification models. The statistically driven logistic regression model was utilized as the classification model in this study, for which a K-fold cross-validation approach was adopted where K was chosen as 10.

3. Results

The results in Table 1 show the accuracies in the model prediction of labor imminency across the various patients, from which it can be seen that the DWS produced an accuracy of 62.7% This is lower than the other methods, which produced accuracies of 90% and 70% respectively. This indicates that, unlike previous works, the DWS does not appear to be optimal to this application. Reasons for this remain subject to further research, but interim beliefs are based around the dynamics of the MMG signal, which make it unfeasible for effective analytics with the DWS. In contrast, the LSDL produced a much better performance. However, there are benefits and positives associated with the use of each method; for example, the DWS does provide the benefit of enabling for an unsupervised feature extraction process, which in turn negates the need for expert knowledge within that segment of the signal processing phase.

Table 1. Accuracies, merits and demerits of the models in predicting labor imminency.

Method	Accuracy (%)	Merits	Demerits	Reference
DWS	62.7	- Unsupervised feature learning - No expert knowledge required	- Relatively low performance accuracy - No feature interpretations	Present study
LSDL + Handcrafted Features	90	- Computationally effective multiresolution decomposition - Optimal for this application as evidenced by accuracy	- Arduous tuning required for parameter initialization for the LSDL - Requires expert knowledge of features	[7]
Handcrafted Features Only	70	- Less processing time - Sparse tuning and parameter setting required	- Requires expert knowledge of features	[7]

4. Conclusions

This work has investigated the notion of utilizing largely uninvestigated and novel means of signal processing towards the prediction of labor imminency, from a set of MMG signals. The DWS was investigated for the first time for the unsupervised feature learning and extraction prior to modelling of the signal with the use of a machine learning model. The results of this were contrasted with the LSDL + Handcrafted features and Handcrafted Features Only, where it was seen that for the LR model used, the DWS carried a slightly less accurate classification accuracy score under the various modelling conditions, albeit with the caveat of having a more streamlined process due to having an unsupervised component as part of its architecture.

In an attempt to optimize and improve the classification accuracy of the DWS's predictions, further work would now involve the application of various other kinds of models towards investigating to see which models provide the best pattern recognition results for the DWS.

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