


Proceeding Paper

# Bio-Magneto Sensing and Unsupervised Deep Multiresolution Analysis for Labor Predictions in Term and Preterm Pregnancies <sup>†</sup>

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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 to predict 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 deliveries with an 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 in the postprocessing and decomposition of MMG signals. This work requires a degree of expert knowledge and an understanding of tuning and parameter initialization. As a stride towards creating a more automated clinical decision support platform for predictions of preterm labor, we employ the use of a deep wavelet scattering (DWS) model. This methodology allows for a deep multiresolution analysis alongside unsupervised feature learning for the postprocessing of candidate MMG signals. DWS is combined with select pattern-recognition-based prediction machines in order to assemble a clinical decision pipeline for the prediction of the states of various pregnancies, with a greater degree of machine intelligence. The patient cohort consisted of a multi-ethnic demographic population composed of preterm and term pregnancies, where births occurred both under and over 48 h after labor commenced. Contrasting results were found between the various methods from the literature and DWS using the logistic regression algorithm. It was seen that DWS produced a slightly lower accuracy in comparison, as a trade-off for its streamlined unsupervised feature extraction process. Further work will now involve the application of various other machine learning methods in an attempt to assess and identify the most appropriate machine learning method with DWS that proves to be the most accurate.

**Keywords:** maternal care; signal decomposition; machine learning; signal processing; pregnancy; magneto sensing; electrodynamic; LSDL



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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 births, can occur during this process [1–3]. It is important to identify potential preterm births in order 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 in an analytical prediction of potential labor and an inference for a preterm birth [1]. As the uterine wall itself is a muscle, its involuntary contractions take place with ionic current flows, which are electrophysiological manifestations that can be measured from either a bioelectric or biomagnetic perspective [4]. The affordability and relative ease of acquisition of measurements via electrohysterogram (EHG) signals means that the majority of recordings come from a bioelectric perspective [1]. However, the limitations of EHG signals are based around the attenuation of the bioelectrical signals as they steadily travel through tissue from the source contractions to the receivers [1]. Regarding the orthogonal counterpart, the magnetic offset can be acquired with a magnetomyography (MMG) instrument which is robust from the aspect of tissue conductivities [4].

Prior studies into the use of MMG for the prediction of labor imminency has been performed by Eswaran et al. [5], who adopted a high-resolution superconducting quantum interference device array for reproductive assessments (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 areas of research relating to this topic, including by the author of this paper alongside various signal processing and machine learning models towards improved predictions of imminent labor cases [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]. Deep wavelet scattering (DWS) comprises a merger between convolutional neural networks (CNNs) from the deep learning architecture and 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 its performance with the 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 contain two class labels, which correspond to patients whose labor was completed within 48 h of the MMG acquisition measurements, and those whose labor lasted over 48 h [9]. The data were 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 performed as part of this study.

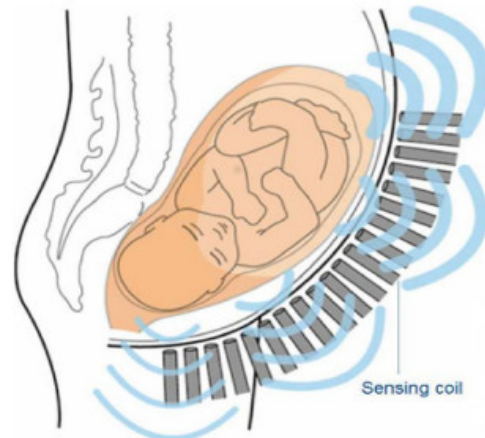
A database containing further information on the data acquisition process, ethical approval and patient information consent, can be seen on the Physionet website [9].

### 2.2. Methods

#### 2.2.1. DWS

DWS is capable of extracting unsupervised features that are continuous and mostly robust to translations whilst comprising features of both wavelet decomposition and CNNs [8]. For 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 was proposed by Andén and Mallat [8], where the computational interpretation of 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 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 eight wavelets per octave in the first filter bank, followed by one wavelet per octave in the second filter bank.



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

### 2.2.2. Linear Series Decomposition Learner (LSDL)

In order to benchmark and contrast the performance of DWS, results of the LSDL from the literature were also included. The LSDL is a metaheuristically driven method which is capable of separating a candidate signal into multiple components with a view towards finding the optimal region in a signal that 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 inception study for the LSDL was based on a source separation exercise involving a heterogeneous mixture of powders which produced highly variable nonlinear signals, for which the LSDL appeared adept at estimating, the results of which superseded classical wavelet decomposition [11–14]. The LSDL has been adopted in a multitude of other studies in 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

To form a contrastive basis for the results from 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, fourth 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 of the model prediction of labor imminency across the various patients, from which it can be seen that 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, DWS does not appear to be optimal in this application. The 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 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 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 in the prediction of labor imminency from a set of MMG signals. DWS was investigated for the first time for 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 methods, where it was seen that for the LR model used, DWS had a slightly lower accurate classification accuracy score under 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 DWS's predictions, further work will now involve the application of various other kinds of models to investigate which models provide the best pattern recognition results for DWS.

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