Combining Electrohysterography and Heart Rate Data to Detect Labour

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***Abstract*— In this paper we propose a method combining electrohysterography (EHG) and heart rate (HR) data to detect labour. Labour detection may be helpful in providing just in time care and avoiding unnecessary antenatal visits. Given specific changes in physiological data such as EHG and HR highlighted from previous literature in correspondence of uterine contractions, we sought to create a model able to classify between labour and non-labour recordings based on EHG and maternal HR data. In particular, we collected 37 recordings (19 labour and 18 non-labour) from pregnant women at different stages of pregnancy using a wearable sensor designed to be attached to the abdomen using an adhesive patch. We extracted time and frequency domain features from EHG and HR data, as stronger, sinusoidal patterns arise on both data streams in correspondence with uterine contractions during labour. Features were used as input to a random forests classifier, trained to recognize labour and non-labour recordings. The accuracy of the proposed model in classifying labour and non-labour recordings was evaluated using leave one out cross validation. We analyzed results including as predictors; gestational age (GA) only, as reference lower bound (68% accuracy), EHG features only (71% accuracy), HR features only (71% accuracy) and combined EHG and HR data, resulting in 82% accuracy. Inclusion of GA as additional predictor further increased detection accuracy to 79%, 82% and 87% for EHG, HR and combined EHG and HR respectively. Our labour detection model demonstrated a high accuracy in classifying labour and non-labour recordings using EHG and HR data collected using a single wearable device.**

I. INTRODUCTION AND RELATED WORKS

Labor is the physiological process during which the fetus is expelled from the uterus and is typically divided into three stages where contractions become more rhythmic and stronger, accompanied by cervical effacement and dilation [1]. To date, labor remains a clinical diagnosis and labour detection remains a challenge as currently used methods for monitoring labor are either subjective or do not provide accurate differentiation between true and false labor.

Labour detection may be helpful in providing just in time care, reducing healthcare costs and providing better care by avoiding unnecessary antenatal visits. Additionally, conditions such as preterm birth and early contractions might be better diagnosed, therefore improving prenatal care and treatment for preterm labour. Preterm labor, defined as labour before 37 weeks gestation, is the most common obstetric complication, occurring in about 20% of pregnant women worldwide, and a major cause of perinatal illness and death. Increased uterine contractions may be a sign of preterm labour, and tocolytic therapy can inhibit the onset of labour, or prolong the pregnancy, giving time for treatment to improve the baby's health. However, many women do not recognize these contractions in time for treatment. If such situations could be identified in the home environment with different monitoring tools, clinical personnel could intervene in a timely fashion and possibly improve health outcomes [2]. Therefore, one of the keys to treating preterm labor would be its early detection or prediction, the main focus of our work. Hospitals often use a pressure transducer (TOCO) placed on the abdomen for basic noninvasive monitoring of uterine activity. However, the TOCO is not a reliable technique [4], [5] and is unable to determine if labour is approaching.

One of the most promising noninvasive markers of labour and preterm labour is the electrical activity of the uterus [6], or electrohysterogram (EHG). EHG has been shown to be representative of uterine contractility and has been considered a very promising tool for different applications, from preterm birth prediction to contraction and labour detection. It is widely accepted that uterine contractions are generated by the electrical activity originating from the depolarization-repolarization of smooth muscle myometrial cells, creating intermittent bursts of spike-like action potentials [7]. This electrical activity is low and uncoordinated early in gestation [5], but becomes intense and synchronized later in pregnancy, peaking at term [8], hence motivating the use of EHG measurements to detect contractions.

Changes in uterine activity that can be measured using EHG are only part of a multitude of alterations in physiology and anatomy occurring during pregnancy [9]. Dramatic changes in cardiac output have been previously reported during labour [10], with an increase up to 12% between contractions and 34% closer to delivery, which might derive from increased stroke volume already starting during the first phase of labour. Additionally, maternal heart rate (HR) accelerations resulted in high amplitude and duration and were synchronized with uterine contractions [11], hence making maternal cardiac activity another non-invasive parameter well representative of physiological changes with labour onset [12].

Wearable sensors able to acquire physiological data noninvasively, together with recent advances in signal processing and machine learning techniques, can finally provide a way to passively and safely investigate changes in EHG and HR during labour and potentially provide pregnant women

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with a new tool able to predict or detect labour outside of the hospital settings. Recent efforts focused on trying to discriminate between term and preterm deliveries using EHG recordings collected early in pregnancy [17]. While reported results are promising, issues on the methodology and oversampling techniques have been raised, as datasets were overfitted [18]. Other studies have shown that the analysis of the propagation, or synchronization, of the uterine electrical activity is a powerful tool to characterize and to discriminate pregnancy and labor contractions, after contractions have been manually isolated [19], [20], [21]. Similarly, the authors in [22] analyzed synchronization between electrically and mechanically measured contractions, reporting higher agreement during labour. To the best of our knowledge, no research to date addressed the issue of classifying physiological measurements (EHG and HR) collected non-invasively during pregnancy in labour and non-labour classes.

Given the physiological changes in uterine and cardiac activity reported in literature during labour, as well as the ability of current technology to reliably measure EHG and HR data noninvasively, we hypothesized that combining EHG and HR data for labour detection could be feasible, and combined EHG and HR data should provide higher accuracy in detecting labour. One of the additional advantages of our proposed approach is that manual (or automatic) segmentation of data into contractions and non-contractions is not needed, as we analyze physiological signals properties over longer periods of time. Thus, in this paper we propose the first work in which time and frequency domain features extracted from EHG and HR signals were combined in order to discriminate labour and non-labour recordings acquired with a single wearable device, analyzing results for different feature sets, including GA, EHG and HR data, and showing optimal results when all parameters are combined, for an overall accuracy of 87%.

II. APPROACH

In this section we describe our approach to discriminate labour and non-labour measurements. In particular, this is a retrospective study in which we aim at extracting features representative of the rhythmic pattern present in both EHG and HR data as a consequence of increased uterine activity. However, we do not manually select contractions but analyze data over longer periods of time to extract features representative of labour without requiring manual data segmentation. In particular, we chose to compute features over windows of 20 minutes, as this time frame is both long enough to capture rhythmic patterns and short enough not to include noise which could be present in longer measurements simply due to maternal movement. Fig. 1 shows an example of EHG and HR data for two subjects, one in labour and one non in labour.

III. DATA ACQUISITION

Thirty-seven recordings were collected from 37 pregnant women at different time points during pregnancy (GA $=$ 37.5 ± 4.4 weeks). Measurements were performed using a research version of the Bloomlife wearable device [23], configured to acquire two channels ExG at 4096 Hz and triaxial accelerometer data at 128 Hz from a single accelerometer placed on the abdomen (see Fig. 2). The Bloomlife wearable sensor was attached to the skin using a medical grade adhesive patch. In this retrospective study we included measurements collected under different conditions. In particular, 12 measurements were collected in home settings and lasted for periods up to 8 hours, 21 measurements were recorded during hospital visits, concurrently with TOCO measurements, while participants were lying down in hospital beds for 1 to 4 hours. The remaining 4 measurements were also collected in hospital settings but with intermittent bed rest and free-living activities. To standardize the analysis, the experimenter manually selected periods of 1 hour per participant, according to the following criteria: accelerometer data showed no ambulatory movement and minimal artifacts and HR data was present for at least 80% of the measurement. Measurements were assigned to the labour class retrospectively based on delivery within 24 hours from the measurement.

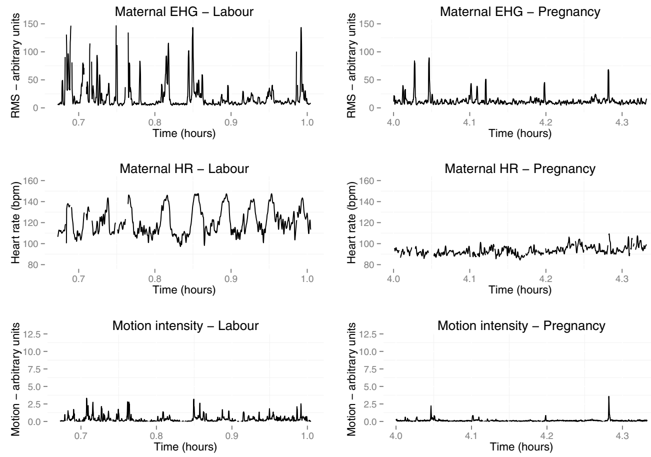

Fig. 1. Example of EHG, HR and accelerometer traces for two segments of 20 minutes collected from two participants, one in labour and one non in labour. Increased EHG activity and rhythmic HR patterns are clearly visible during labour. Accelerometer data is shown as context, as all recordings were selected during periods of no or low motion to avoid artifacts.

Fig. 2. The Bloomlife wearable used to acquire EHG and HR data.

IV. DATA ANALYSIS

A. Pre-processing

For EHG analysis, we first downsampled ExG data to 16 Hz as the EHG signal energy mainly ranges from 0.1 to 3-5 Hz. We then applied a low-pass Finite Impulse Response (FIR) filter (4 Hz cutoff frequency) and a high-pass FIR filter (0.1 Hz cutoff frequency) to isolate the main frequency of interest for EHG data [24]. Similarly, for HR analysis, the first preprocessing step consisted of band-pass filtering the ExG signal between 2 Hz and 98 Hz to remove all out-of-band noise and a notch filter at 50 Hz to remove powerline interference. Maternal R-peak detection was performed based on the algorithm described in [24]. Accelerometer data were bandpass filtered between 1 and 10 Hz to isolate maternal movement.

B. Features Extraction

We extracted two feature sets to be used for classification. First, features were extracted over 16 seconds windows to capture EHG and cardiac properties as they evolve over time. An example of two features can be seen in Fig. 1 where the Root Mean Square (RMS) of the EHG signal and the mean HR over consecutive 16 seconds windows is shown. Features extracted were: RMS of the EHG signal, normalized range of the EHG signal ($\frac{max-min}{\sigma}$, [25]), mean crossing rate of the EHG signal, power of the EHG signal and mean HR. Features were then summarized in terms of mean and standard deviation over 20-minute windows. Additionally, we computed features on the entire 20-minute segment, with the aim of capturing more information relative to the rhythmic pattern present during labour. In particular, we extracted the following features: power of the EHG and HR signal, frequency and amplitude of the main peak (EHG and HR), HR quantiles and max autocorrelation of the HR signal. As a result, each 20 minutes segment was characterized by a set of EHG and HR-derived features, plus GA, for a total of 3 segments per participant. An example of feature distributions is shown in Fig. 3.

C. Classification and Performance Metrics

Models were derived and validated using leave one participant out cross-validation and a binary classification problem distinguishing labour from non-labour. We chose random forests as classifiers and did not perform feature selection as during training random forests pick a subset of the available features at each iteration, therefore exploiting information present in the many features included in this study without having to reduce the feature space. Given the balanced dataset (19 labour and 18 non-labour) and only two classes, we used *accuracy* as the only metric to report results. We fed the random forests seven different feature sets, in order to analyze differences in accuracy for EHG, HR, combined EHG and HR and also GA as an additional feature, starting from a lower bound on accuracy provided by using only GA as predictor. We computed features over 20 minutes segments, for a total of 3 segments per participant (1 hour of data). Thus, we performed leave one subject out cross-validation by excluding at each iteration the 3 segments belonging to the participant to be validated. Finally, we used majority voting on the 3 predictions to assign a class to each participant.

V. RESULTS

Results of subject-independent cross-validation of the different models analyzed in this study, based on EHG, HR and GA features, are shown in Fig. 4. In particular, we first computed results for a model including GA as the only feature, in order to provide a lower bound on the model accuracy for our dataset. Results for this model including only GA as predictor were 68% accuracy, for EHG features only were 71% accuracy, HR features only were 71% accuracy and combined EHG and HR data were 82% accuracy. Hence, a combined approach provided the highest accuracy. These results provide confirmative findings on the consistent physiological changes in both EHG and HR data during labour. Inclusion of gestational age (GA) as additional predictor further increased detection accuracy to 79%, 81% and 87% for EHG, HR and combined EHG and HR respectively, providing very good results for the combined approach (EHG, HR and GA features).

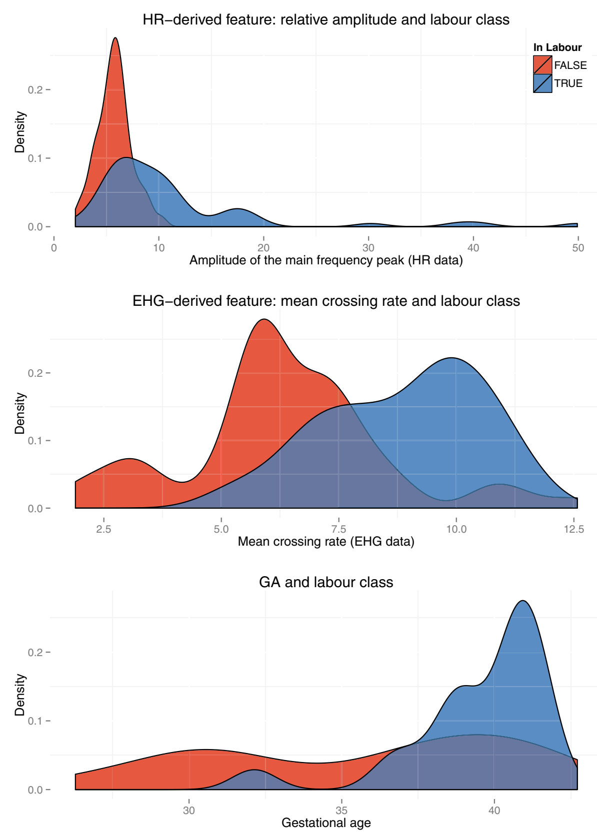

Fig. 3. Density distributions for one EHG-derived (mean crossing rate) and one HR-derived feature (relative amplitude) with respect to the labour class. We can see expected behavior with higher relative amplitude in HR data for labour cases, as well as increased mean crossing rate for EHG data. GA shows that included measurements for the non-labour class span over several weeks, including the last few days of pregnancy.

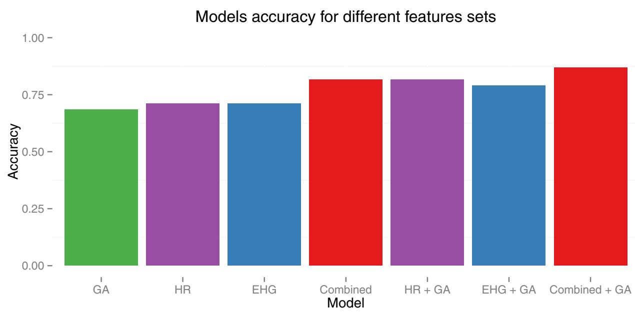

Fig. 4. Accuracy for different combinations of features. *Combined* includes EHG and HR data. Including GA consistently improves detection. EHG and HR data perform similarly, and the best results are obtained when combining data streams (87% accuracy).

VI. CONCLUSIONS

During labour, more dramatic physiological changes occur with respect to pregnancy, for example the increase in gap junctions elicits physiological processes that influence EHG activity. As the uterus prepares to expel the fetus, changes in both EHG and cardiac activity were highlighted in previous literature in correspondence with uterine contractions. In this work we proposed a method combining EHG and HR features computed over 20-minute windows to detect labour without requiring manual segmentation of contractions data. We showed that the different physiological patterns could be captured by the proposed model, classifying labour and non-labour measurements with 87% accuracy. We also provided as comparisons results obtained only when one data stream is available, and with or without GA, ranging from 68% to 82% accuracy. Building on the proposed work, labour detection may be helpful in future research not only in providing just in time care and avoiding unnecessary antenatal visits, but potentially to provide better care for preterm birth. Our future work will focus on collecting more combined EHG and HR data in unsupervised free-living settings, longitudinally for each individual. Longitudinal data could provide additional insights with respect to labour onset on within-individual physiological changes that cannot be captured with cross-sectional data including only one recording per participant.

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