Identification of Uterine Contractions by an Ensemble of Gaussian Processes

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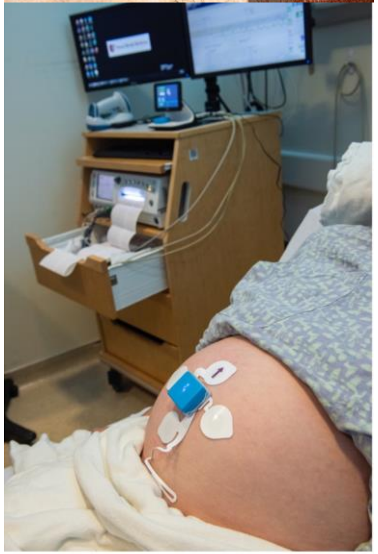
Overview

- ❖Motivation
- ❖Problem Description
- ❖Model and Method
- ❖Experiments
- ❖Conclusions

Motivation

- Electronic fetal monitoring records both fetal heart rate (FHR) and uterine activity (UA) signals.
- Automatic FHR analysis assists clinicians to reduce the risk of fetal hypoxia and acidosis with timely surgical interventions during labor.
- With the fact that UA causes FHR, the identification of uterine contractions can guide us for advanced FHR interpretation.

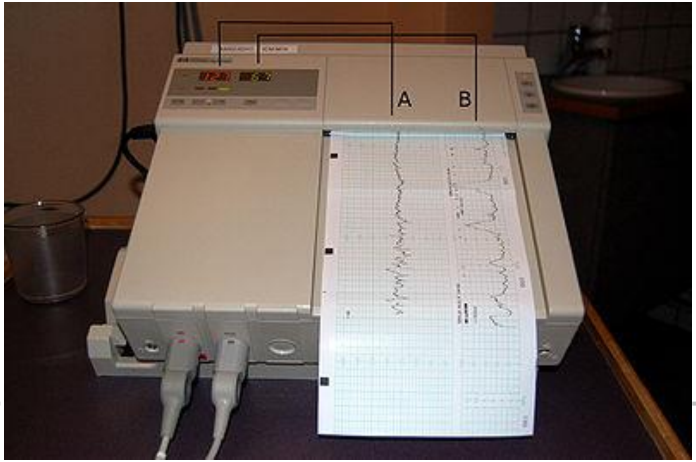


Picture source:
https://www.stonybrook.edu/commcms/electrical/research/2021/djuric.php

Problem Description

One of the common approaches for UA monitoring is tocodynamometry (TOCO), which is an external monitoring.

The TOCO UA signals are usually noisy with unstable resting tones and intensive jiggling.



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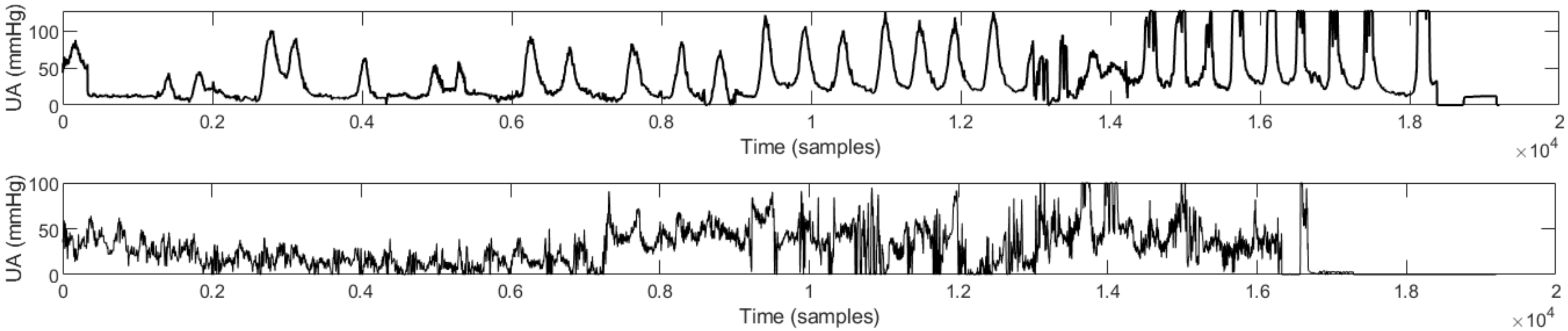

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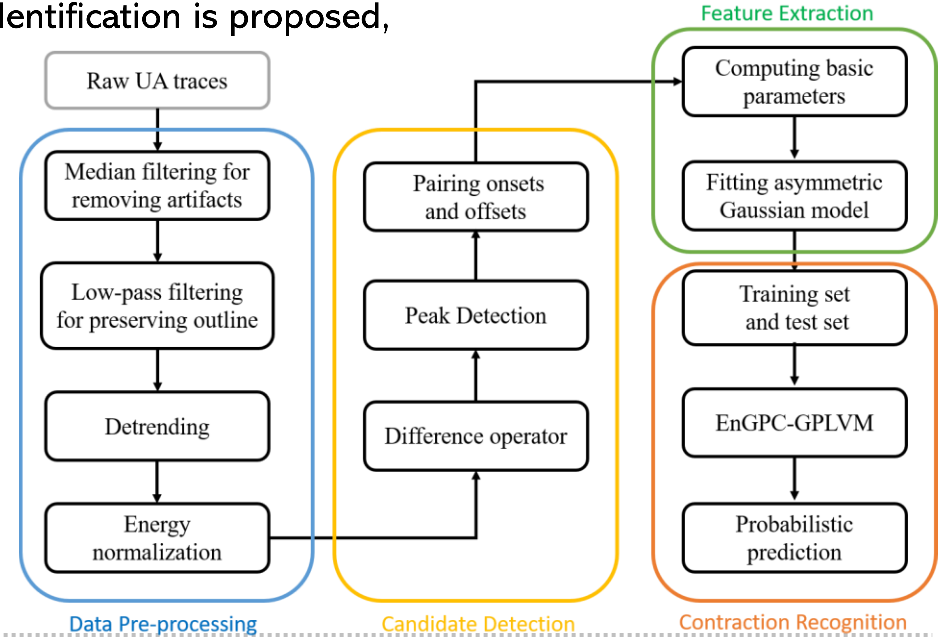
Model and Method

A method for uterine contraction identification is proposed, which includes four main steps:

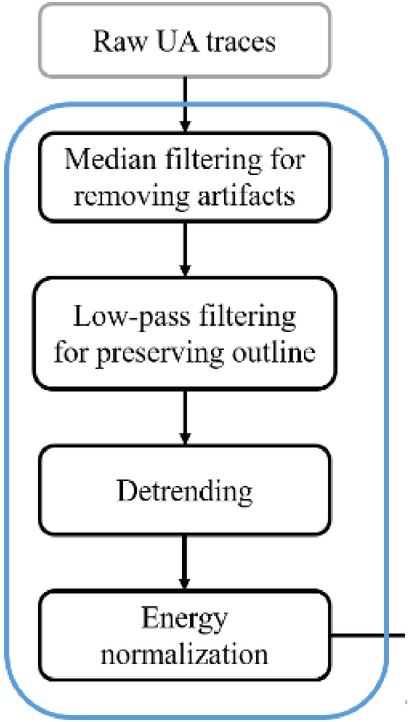
I. Data pre-processing
II. Candidate detection
III. Feature extraction
IV. **Contraction recognition**



Model and Method

Step1: Data pre-processing

Since the typical sampling rate of UA signal is 4Hz, we take it as an example and design the filters.



Data Pre-processing

Model and Method

Step1: Data pre-processing

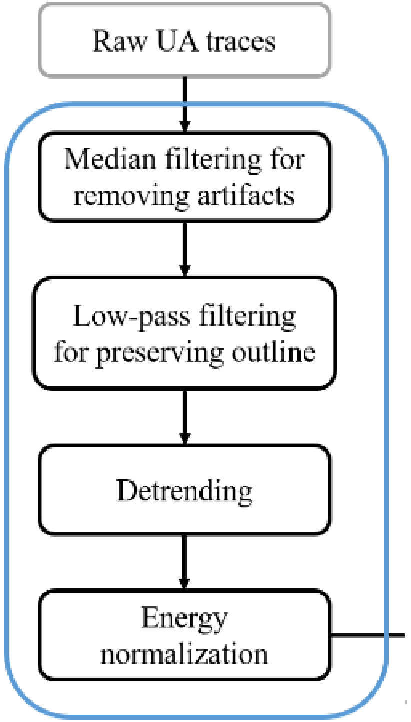
Since the typical sampling rate of UA signal is 4Hz, we take it as an example and design the filters.

30-seconds 1D median filter

Zero-phase low-pass filter with cutoff frequency 0.04Hz

6-min 1D median filter

Normalization in a moving 6-min window



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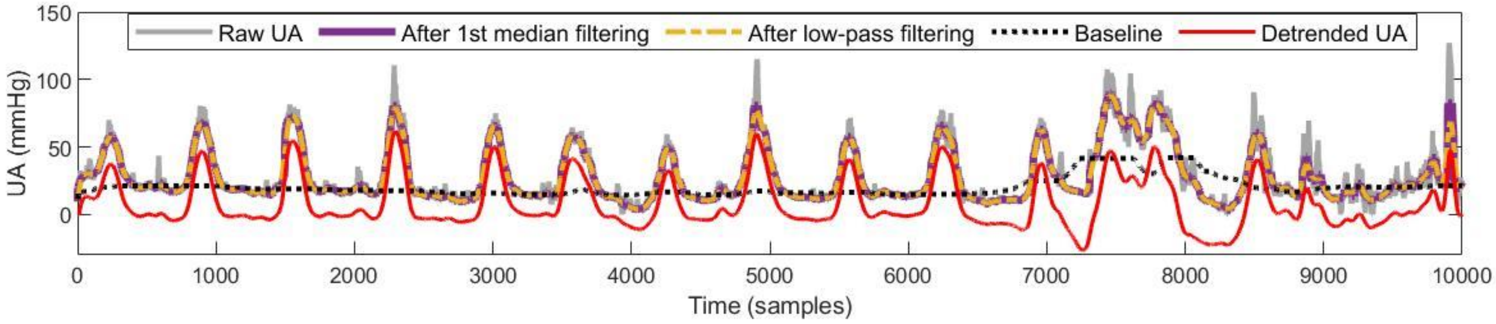
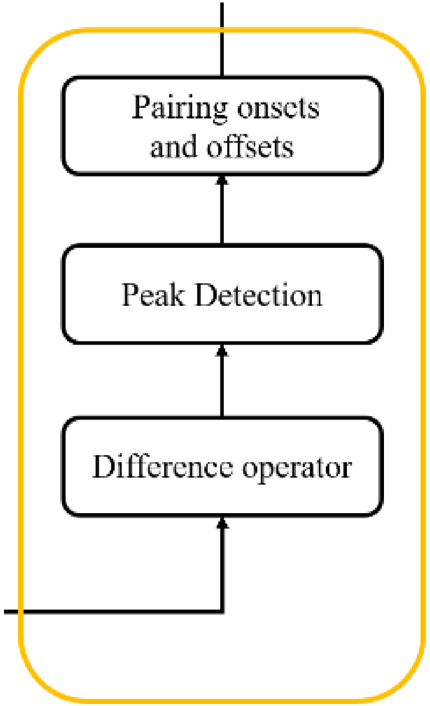


Model and Method

Step2: Candidate detection

difference operator d[n]=x[n+delta]-x[n]   delta=0.4min/0.6min



Candidate Detection

Model and Method

Step2: Candidate detection

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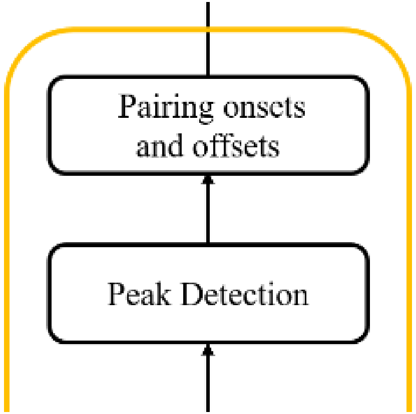

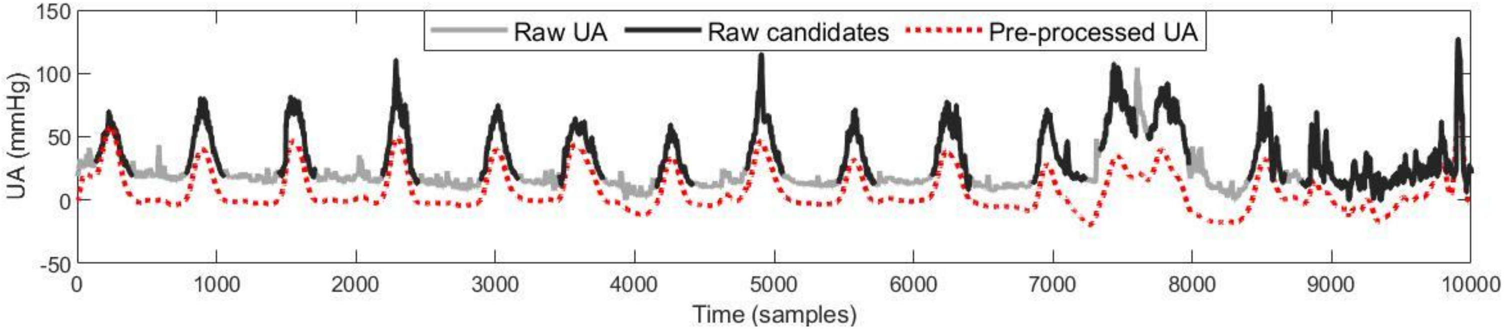

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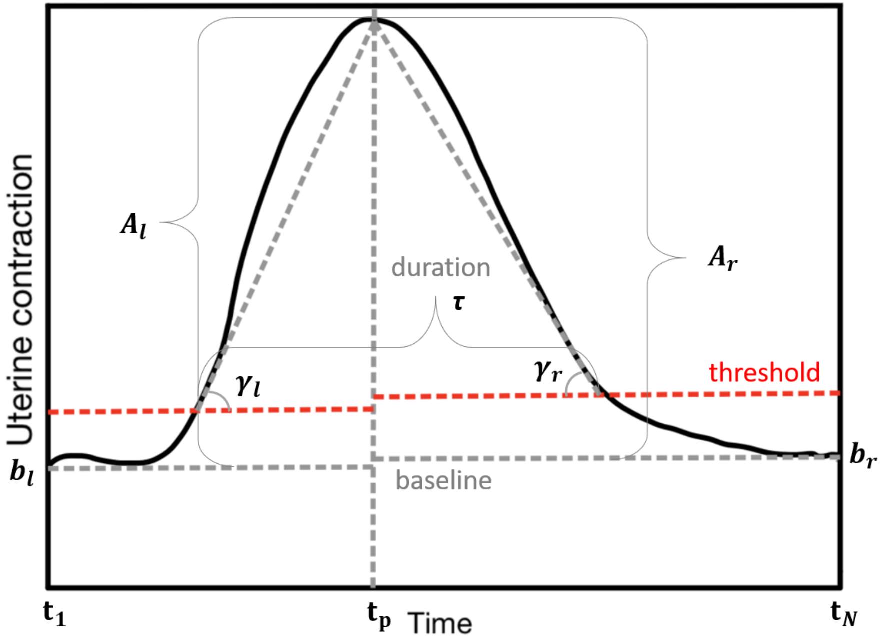
Model and Method

Step3: Feature extraction

τ	Duration
A	Mean of A_l and A_r
$\tan(\gamma_l)$	Left slope
$\tan(\gamma_r)$	Right slope



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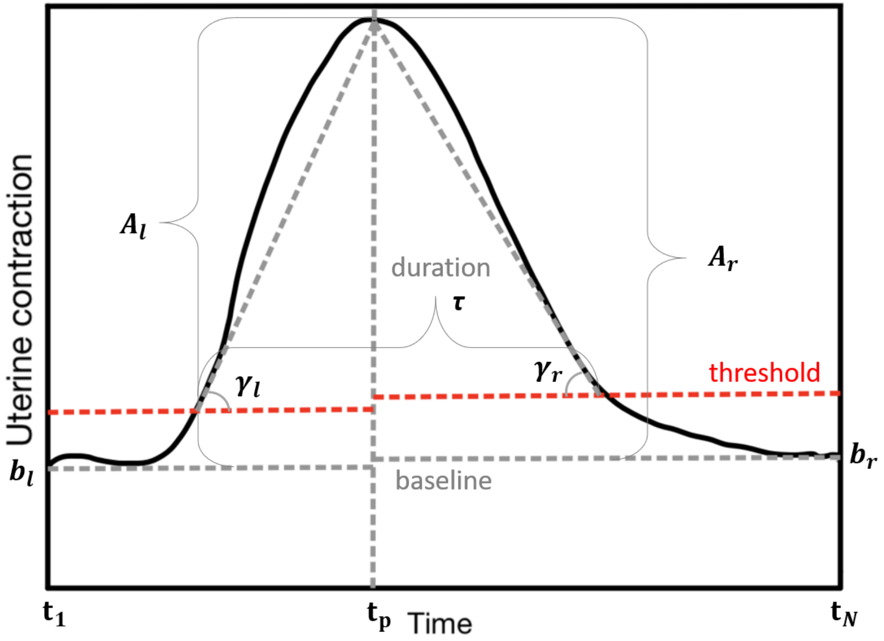
Model and Method

Step3: Feature extraction

Asymmetric generalized Gaussian model:

$$f(t) = [b_l + A_l \exp(-\frac{|t-t_p|^{\alpha_l}}{\beta_l})][u(t-t_1) - u(t-t_p)]$$

$$+[b_r + A_r \exp(-\frac{|t-t_p|^{\alpha_r}}{\beta_r})][u(t-t_p) - u(t-t_N)]$$



Model and Method

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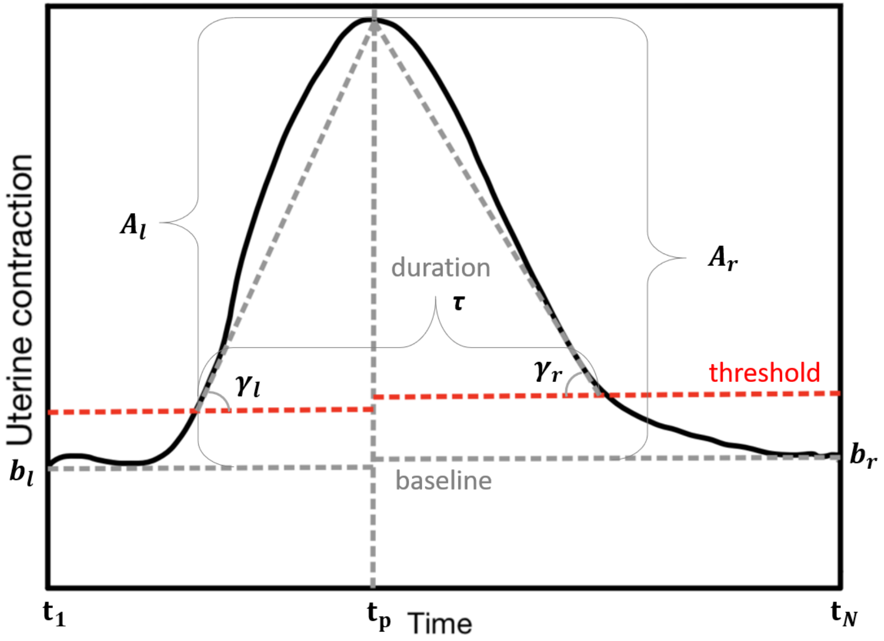
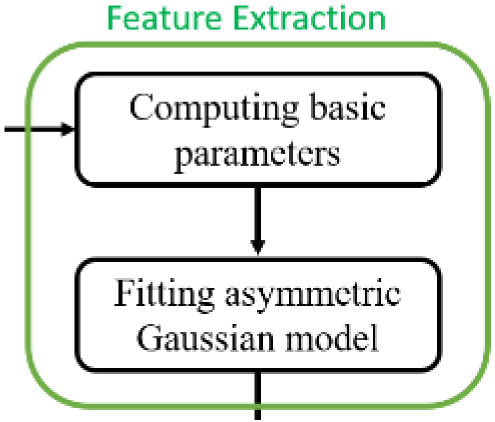
α_l	Shape
β_l	Shape
α_r	Shape
β_r	Shape



Model and Method

Step3: Feature extraction



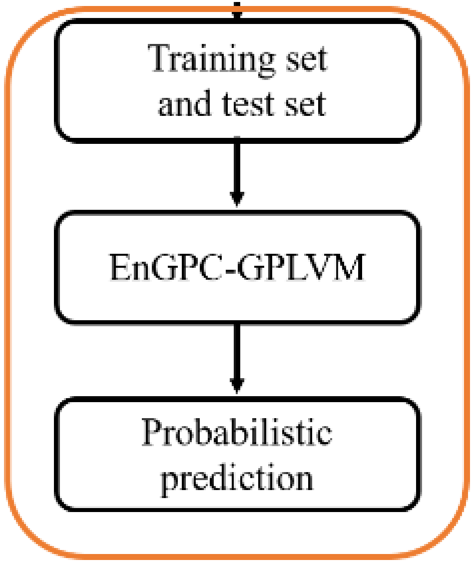
Basic	τ, A, $\tan(\gamma_l)$, $\tan(\gamma_r)$	Shape	α_l, β_l, α_r, β_r

Model and Method

Step4: Contraction recognition

Since most of the candidates should be contractions,
it can be formulated to an imbalanced classification problem.

According to [1], we applied the EnGPC-GPLVM to predict the probabilities of every candidates being contractions.



Contraction Recognition

[1] L. Yang, C. Heiselman, J. G. Quirk and P. M. Djurić, “Class-imbalanced classifiers using ensembles of Gaussian processes and Gaussian process latent variable models", in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., ICASSP-2021

Model and Method

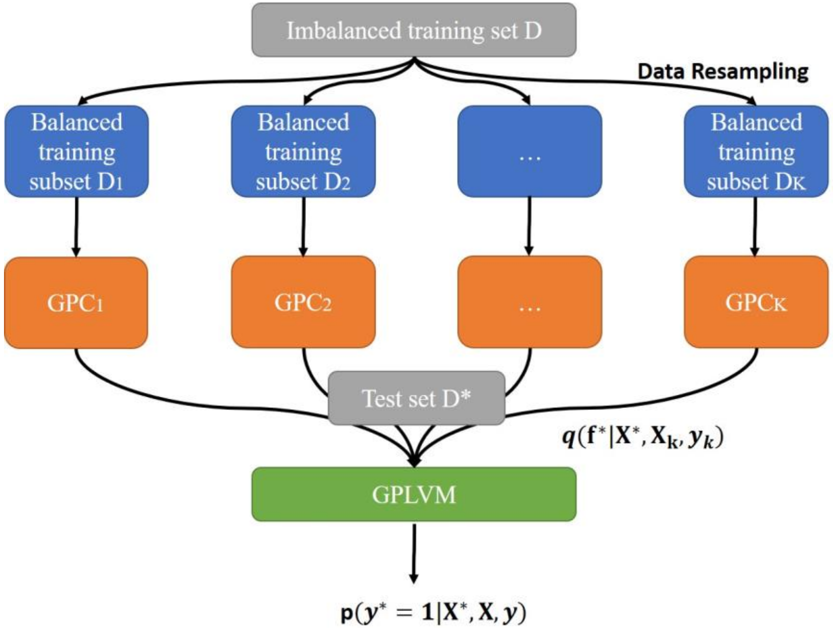
Step4: Contraction recognition

Training set $\mathcal{D} = \{\mathbf{X}, \mathbf{y}\}$

$\mathbf{X} \in \mathbb{R}^{dx \times n}$ $\mathbf{y} \in \mathbb{R}^{n}$

Each column of X contains all features of a candidate sample.

Test set $\mathcal{D}^* = \{\mathbf{X}^*, \mathbf{y}^*\}$



Model and Method

Step4: Contraction recognition

Each GPC, as an expert
gives its "opinion"
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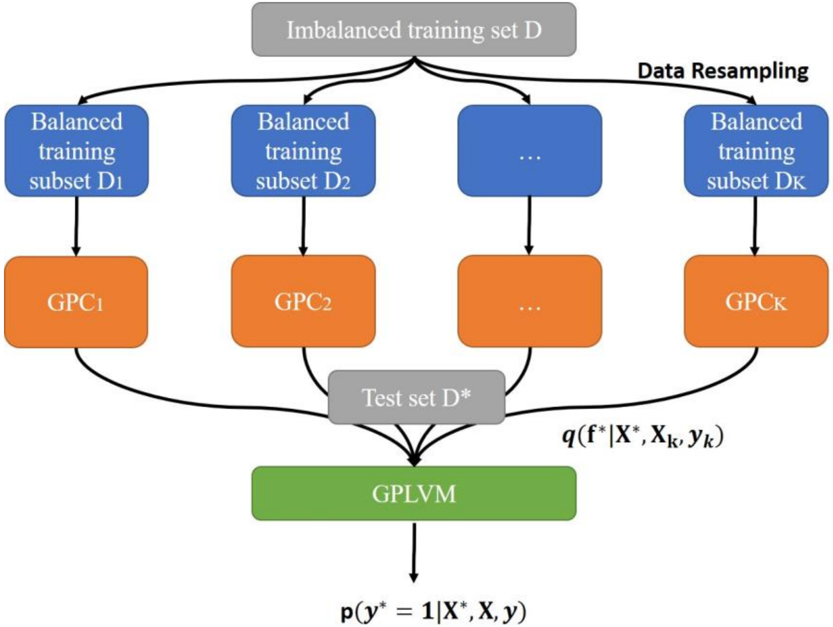

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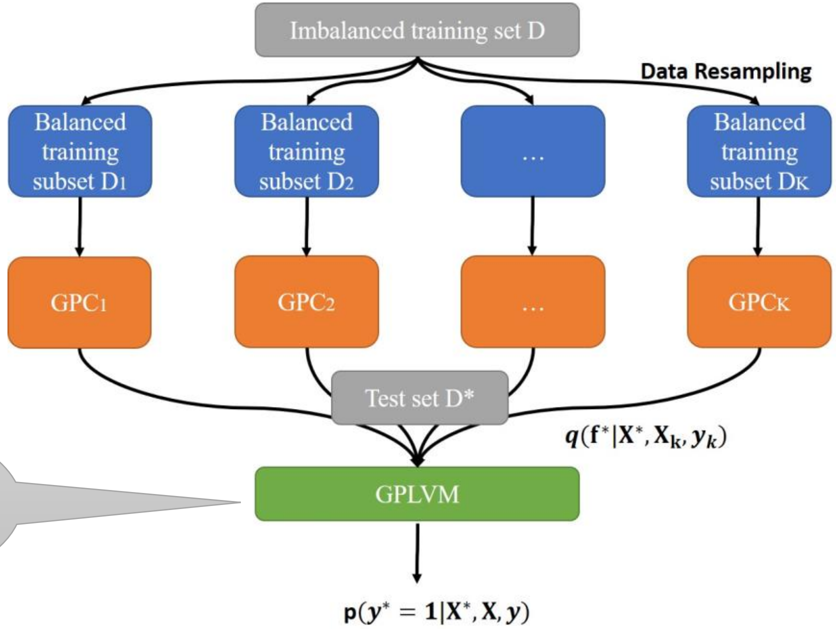
Model and Method

Step4: Contraction recognition

Each GPC, as an expert gives its "opinion" about latent values f*.

GPLVM is a senior decision maker who synthesizes all opinions to give a final decision.



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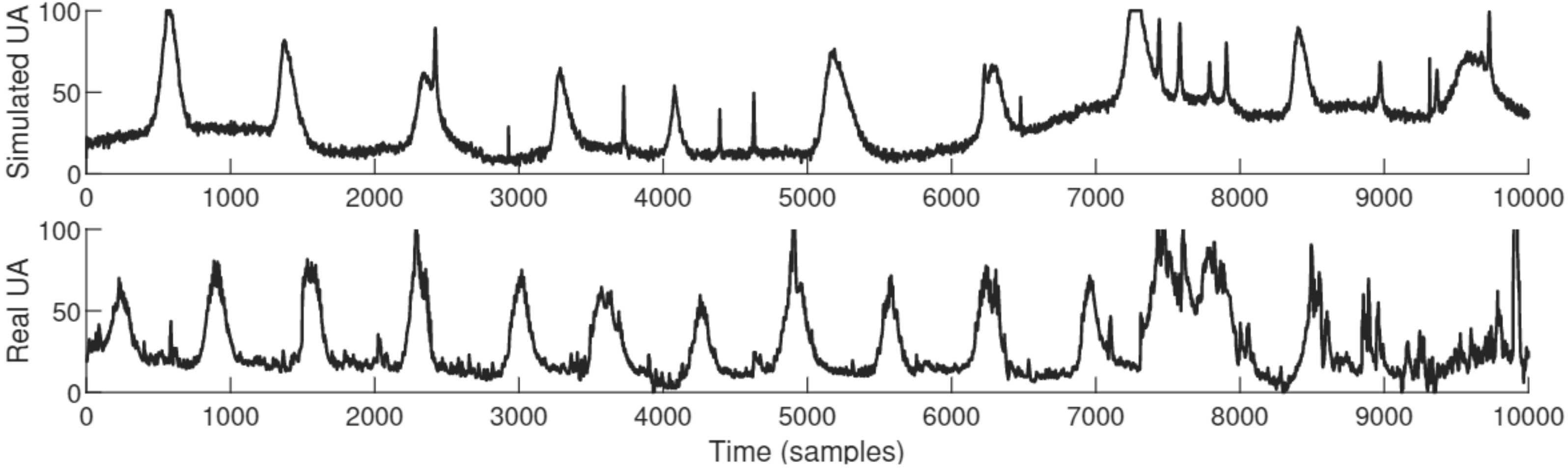
Experiments

Test with simulated UA signals

UA = Baseline + Contractions + Perlin Noise + Impulsive Noise



[2] M. Liu, L. A. Belfore, Y. Shen and M. W. Scerbo, "Uterine contraction modeling and simulation," in *MODSIM World 2009 Conference and Expo Virginia Beach*, 2010, pp.135-140.

Experiments

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Training set : 187 positive samples and 26 negative samples
Test set : 109 samples per class

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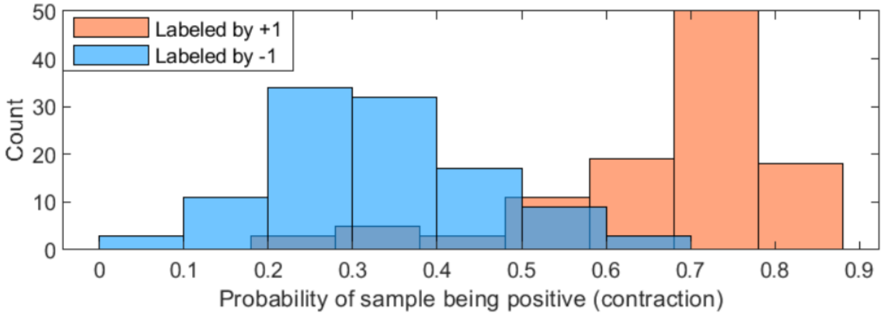


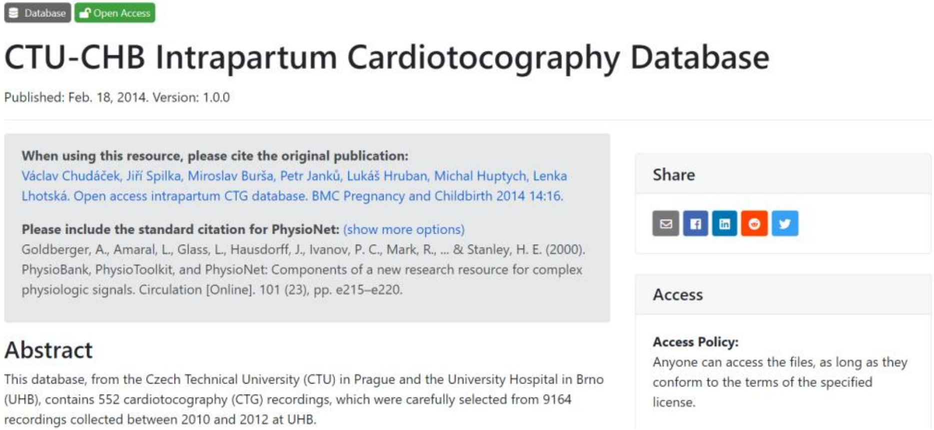
Methods	TPR	FPR	TNR	FNR	F-score
GPC	**0.9725**	0.7523	0.2477	**0.0275**	0.7138
EGPC-Avg	0.9174	0.2018	0.7982	0.0826	0.8658
EGPC-GPLVM	0.8899	**0.1101**	**0.8213**	0.1320	**0.8847**

GPC: only using a GPC-based model on imbalanced dataset
EGPC-Avg: ensemble of GPCs whose outputs are averaged
EGPC-GPLVM: ensemble of GPCs whose outputs are synthesized by a GPLVM.

Experiments

Test with real UA signals

Real UA data from an open access database (CTU-CHB Intrapartum Cardiotocography Database)
Two of the coauthors from Stony Brook University Hospital annotate the training data.



Database Open Access

CTU-CHB Intrapartum Cardiotocography Database

Published: Feb. 18, 2014. Version: 1.0.0

When using this resource, please cite the original publication:
Václav Chudáček, Jiří Spilka, Miroslav Burša, Petr Janků, Lukáš Hruban, Michal Huptych, Lenka Lhotská. Open access intrapartum CTG database. BMC Pregnancy and Childbirth 2014 14:16.

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Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

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Access

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Abstract

This database, from the Czech Technical University (CTU) in Prague and the University Hospital in Brno (UHB), contains 552 cardiotocography (CTG) recordings, which were carefully selected from 9164 recordings collected between 2010 and 2012 at UHB.

Data source: https://physionet.org/content/ctu-uhb-ctgdb/1.0.0/

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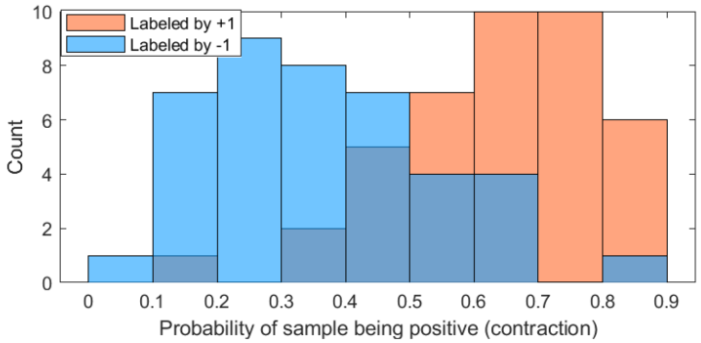

Training set: 233 positive samples
46 negative samples
Test set: 41 samples per class

Methods	TPR	FPR	TNR	FNR	F-score
GPC	**0.9012**	0.3171	0.6829	**0.1488**	0.7387
EGPC-Avg	0.7561	0.1950	0.8049	0.2439	0.7850
EGPC-GPLVM	0.8049	**0.1195**	**0.8293**	0.1951	**0.8148**

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Conclusions

- We tackled the problem of uterine contraction identification from raw and noisy TOCO UA signals.

- A four-step method is proposed where the problem is finally transformed to a task of class-imbalanced classification.

- A GPLVM-based ensemble of GPCs is proposed and used in this work.

Thank you very much for your attention!

Contacts

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†{cassandra.heiselman, j.gerald.quirk}@stonybrookmedicine.edu