

Estimation of Fetal Blood Oxygen Saturation from Transabdominally Acquired Photoplethysmogram Waveforms*

Kourosh Vali¹, Begum Kasap¹, Weitai Qian¹, Ata Vafi¹, Mahya Saffarpour¹, and Soheil Ghiasi¹

Abstract—Transabdominal Fetal Pulse Oximetry (TFO) faces several challenges, including the acquisition of noisy Photoplethysmogram (PPG) signals that contain a mixture of maternal and weak fetal information and scarcity of the data points on which an estimation model can be calibrated. This paper presents a novel algorithm that addresses these problems and contributes to the estimation of fetal blood oxygen saturation from PPG signals sensed through the maternal abdomen in a non-invasive manner. Our approach is composed of two critical steps. First, we develop methods to approximate the contribution of pulsating and non-pulsating fetal tissue from the sensed mixed signal. Furthermore, we leverage prior information about the system under observation, such as the physiological plausibility of fetal SpO₂ estimates, to mitigate measurement noise and infer additional data samples, enabling improvements in the inferred SpO₂ estimation model. We have validated our approach *in-vivo*, using a pregnant sheep model with a hypoxic fetal lamb. Compared with gold standard SaO₂ obtained from blood gas analysis, our fetal SpO₂ estimation algorithm yields the cross-validation mean absolute error (MAE) of 6.29% and correlation factor of $r = 0.82$.

Clinical relevance—Cardiotocography (CTG) is a widely used tool employed by the physician to assess fetal well-being intrapartum non-invasively. There is ample evidence that CTG has a high rate of false positives for detecting fetal hypoxic distress and has contributed to the rise of emergency C-section deliveries. Our work aims to address this problem in the longer term by taking important steps towards developing a non-invasive fetal monitor that can accurately detect fetal hypoxic distress intrapartum.

I. INTRODUCTION

Transabdominal fetal pulse oximetry (TFO) can assist physicians to reliably detect fetal hypoxic distress intrapartum, especially when the fetal heart rate traces captured by existing electronic fetal monitors are deemed indeterminate.

Fundamentally, TFO relies on a similar underlying principle as conventional pulse oximetry. However, since TFO leverages light propagation through maternal and fetal tissue and sensing the diffused light by optical photodetectors placed on the maternal abdomen, it is considerably more challenging than conventional pulse oximetry. In particular, certain obstacles such as light attenuation, fetal signal isolation

from the acquired mixed maternal-fetal PPG signal, and patient variability severely impact TFO.

Some of these challenges have been somewhat explored by characterizing light propagation in the maternal and fetal tissue using Monte Carlo simulations [1], [2], and optimizing the optical probe (optode) design to address the patient variability problem [3]. Also, some preliminary work is reported on the extraction of the fetal signal from the mixed signal containing both maternal and fetal signals using signal processing methods, such as adaptive noise cancellation [3], [4], [5], [6]. Due to these hurdles, calibration of the TFO is also challenging, particularly because data collected for TFO is noisy, low volume, and expensive.

This paper presents a novel algorithm to continuously estimate fetal blood oxygen saturation from mixed PPG signals acquired by a novel Transabdominal Fetal Pulse Oximetry device prototype in an IACUC-approved controlled fetal desaturation protocol using the gold standard pregnant ewe model. We have previously shown the correlation between the estimated fetal blood oxygen saturation using Pulse Oximetry from the TFO (SpO_2) with the *in-vivo* SaO_2 measurements over long observation periods [7]. This paper makes critical contributions by enabling continuous SpO_2 readings by the TFO device.

II. METHODS

A. Hypoxic Fetal Lamb Model

Fig. 1 depicts the setup of the experiment in which PPG data was collected. The lamb was instrumented by placing a carotid arterial line to monitor fetal hemodynamics continuously and occasionally measure fetal arterial blood oxygen saturation through Arterial Blood Gas (ABG) analysis of blood samples. During the experiment, the TFO device is placed on the maternal abdomen, and PPG data is recorded [8]. The blood flow to the ewe's uterus is decreased at a controlled rate using an inflatable balloon catheter, thus decreasing the fetal blood oxygen saturation. The experiment was composed of two rounds, in which each round was divided into multiple 10-minute steps. In each step, the mean distal arterial blood pressure was maintained at constant pressure, and three blood draws were performed at 2.5, 5, and 10-min intervals to obtain fetal SaO_2 via ABG [7].

B. Fetal Signal Isolation

Our objective is to obtain continuous, and physiologically plausible readings of fetal SpO_2 from noisy PPG signals acquired that contain a mixture of maternal and fetal information. At a high level, we have to extract the contributions

* This work was supported by the National Science Foundation(NSF) Grant No. IIS-1838939, the National Institutes of Health (NIH) award R21HD097467 and UC Davis CeDAR.

¹ K. Vali, B. Kasap, W. Qian, A. Vafi, M. Saffarpour, and S. Ghiasi are with the Department of Electrical and Computer Engineering, University of California Davis, One Shields Avenue, Davis, CA, USA (email of the corresponding author: kvali@ucdavis.edu)

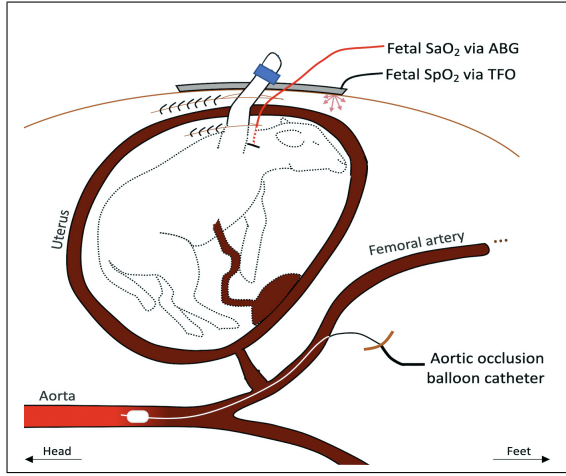


Fig. 1: Transabdominal Fetal Pulse Oximetry (TFO) in a hypoxic fetal lamb experiment.

to the mixed PPG signals that are strictly due to the fetal tissue, and utilize it in the pulse oximetry estimation model to derive modulation ratio (R).

$$R = \frac{\Delta A^{\lambda_1}}{\Delta A^{\lambda_2}} = \frac{\log(I_{sys}^{\lambda_1}/I_{dia}^{\lambda_1})}{\log(I_{sys}^{\lambda_2}/I_{dia}^{\lambda_2})} = \frac{\log(1 + (AC^{\lambda_1}/DC^{\lambda_1}))}{\log(1 + (AC^{\lambda_2}/DC^{\lambda_2}))} \approx \frac{(AC/DC)^{\lambda_1}}{(AC/DC)^{\lambda_2}} \quad (1)$$

The relationship between the modulation ratio (R) and the systolic and diastolic features in the PPG signals collected at the two wavelengths λ_1 and λ_2 , is developed for conventional pulse oximetry, in which the signal's AC component is a variation with about 2-10% amplitude compared to the DC component [9], [10], [11].

In contrast, in TFO, the AC component corresponding to the fetal arterial pulsation is measured to be several orders of magnitude smaller than the DC component, which gives rise to challenges such as calculation errors and insensitivity of the model to the oxygen level variations in fetal blood. Thus, proper scaling needs to be applied before using the measured modulation ratio (R) for fetal SpO_2 estimation. This happens because the measured DC component, which relates to the diastolic cycle in conventional pulse oximetry, is a mixture of the DC component from both maternal and fetal tissue in TFO, as the light traverses through both tissue layers. Although the different rates of pulsation between maternal and fetal heart rates may help separate the two AC components, such information is unavailable to separate their mixed DC components.

To solve this problem, we approximate the DC component from the non-pulsating fetal tissue to be proportional to the relative strength of the measured AC component from the fetal arterial pulsation to the AC components from both fetal and maternal arterial pulsation. As such for λ_1 and λ_2 the ratios are $\alpha = AC_F^{\lambda_1}/(AC_M^{\lambda_1} + AC_F^{\lambda_1})$ and $\beta = AC_F^{\lambda_2}/(AC_M^{\lambda_2} + AC_F^{\lambda_2})$ respectively. We calculate the

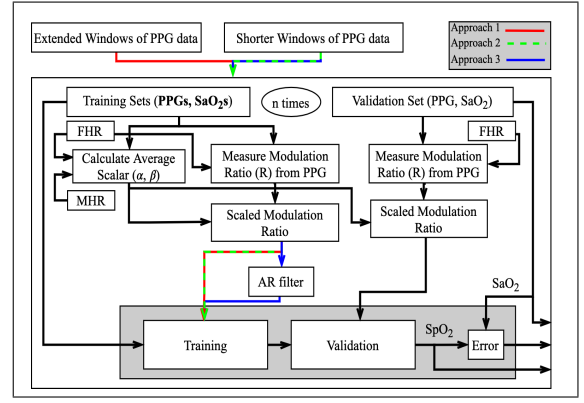


Fig. 2: Block diagram of the proposed algorithm. The validation result is calculated using Leave-One-Out Cross-validation error.

average relative power of the measured light due to the fetal arterial pulsation relative to the maternal pulsation in the PPG power spectrum ($\bar{\alpha}$ and $\bar{\beta}$). We propose to use this ratio to scale the DC component for each wavelength in (1).

$$DC_F^{\lambda_1} \approx \bar{\alpha} \times DC^{\lambda_1} \\ DC_F^{\lambda_2} \approx \bar{\beta} \times DC^{\lambda_2} \quad (2)$$

This factor will depend on the wavelength used to collect PPG and on the specific subject. Note that the fetal depth and the thickness of maternal tissue layers will vary across patient populations. Still, they are available in real-time from independent ultrasound measurements and/or patient history.

C. SpO_2 Estimation From Isolated PPG

Conventional pulse oximetry calculation deals with a single body, and SpO_2 is approximated to have the following relationship with the modulation ratio (R) [12]. In (3), molar extinction coefficients (ϵ) are known for the oxy-hemoglobin (HbO), and deoxy-hemoglobin (Hb) [14], and the two light sources of red and near-infrared (NIR) [15] are used as the red light is sensitive to changes in deoxy-hemoglobin and the NIR is sensitive to changes in oxy-hemoglobin [8], [2].

$$SpO_2 = \frac{\epsilon_{Hb}^{\lambda_1} - \epsilon_{Hb}^{\lambda_2} R(B^{\lambda_2}/B^{\lambda_1})}{\epsilon_{Hb}^{\lambda_1} - \epsilon_{HbO}^{\lambda_1} + (\epsilon_{HbO}^{\lambda_2} - \epsilon_{Hb}^{\lambda_2}) R(B^{\lambda_2}/B^{\lambda_1})} \quad (3)$$

The light pathlength factor, B , can theoretically be estimated by solving the photon diffusion equation for the appropriate measurement geometry and wavelength used [2]. We assume that this factor is mostly constant throughout the monitoring and can be learned as a parameter from data in the model $SpO_2 = f(R)$.

Equation (4) is a reformulated version of (3) which is amenable to parameter estimation from experimental data. Here, $c(\epsilon^{\lambda_2})$ is a constant, independent of B factor. Assuming the constant geometry, we have $c(\epsilon^{\lambda_2}) = -\epsilon_{Hb}^{\lambda_2}/(\epsilon_{HbO}^{\lambda_2} - \epsilon_{Hb}^{\lambda_2})$ [14].

$$SpO_2 = c(\epsilon^{\lambda_2}) + \frac{1}{g(\epsilon^{\lambda_2}, B^{\lambda_2}/\lambda_1) + h(\epsilon^{\lambda_2}, B^{\lambda_2}/\lambda_1)R} \quad (4)$$

Fig. 2 visualizes the key steps in the proposed algorithm. This paper focuses on the periods in which the fetal heart rate is distinct from the maternal heart rate and its harmonics. Thus, fetal information is not buried under maternal information in the power spectrum. We also skip (Fetal Heart Rate) FHR estimation from the PPG data and rely on external fetal heart rate readings obtained through hemodynamic monitoring of fetal lamb carotid arterial line (Fig. 1).

D. Noise Suppression and Data Augmentation

We consider three approaches for estimating the fetal blood oxygen saturation from modulation ratio (R), which is continuously measured in sliding time windows.

1) Noise Suppression via Extended Time Windows:

Initially, we investigated averaging over longer periods to reduce variance and improve stability. However, a drawback of this approach is that it would reduce the number of available labeled data points, which will degrade model calibration and SpO_2 estimations. Specifically, we used a window size of 10-minutes, which is equal to the duration of hypoxic steps in the protocol, to find the average estimation of fetal blood oxygen saturation (SpO_2) during that step. Three gold standard fetal arterial blood oxygen saturation (SaO_2) values are available via ABG on blood samples in each step. For each 10-minute step, we averaged the SaO_2 values to obtain one value for the step. Fig. 3 shows the average modulation ratio measurements vs. averaged SaO_2 over one experiment round.

2) Overlapping shorter Windows to Increase Samples:

To have a finer time resolution to estimate and increase the labeled data points, we set the time window to 2.5 minutes with 50% overlaps. This helps TFO report SpO_2 estimations with less delay. To achieve this, we can use the three measured ABG samples within a hypoxic step for training, and we ignore 2.5-minutes time windows in which there is no SaO_2 measurements available. Fig. 4 demonstrates the higher resolution modulation ratio measurements vs. all the SaO_2 samples taken in one round.

3) Leveraging Physiological Plausibility to Reject Noise:

We note that our measurements relate to a living system subject, and therefore, any estimations should be physiologically plausible. For example, changes in fetal blood oxygen saturation have to follow dynamical constraints of oxygen

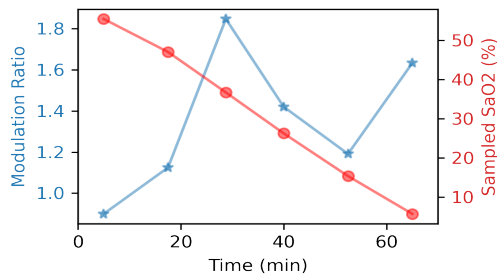


Fig. 3: Averaged Modulation Ratio values (blue) from TFO vs. averaged fetal blood oxygen saturation SaO_2 (red) in this round

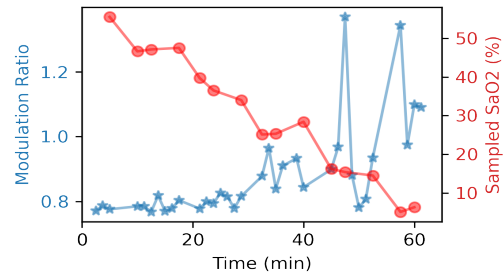


Fig. 4: Higher resolution Modulation Ratio values (blue) from TFO vs. fetal blood oxygen saturation SaO_2 (red) in this round

consumption and diffusion, which bounds the amount of change that would be physiologically plausible from one measurement window to the next.

As such, highly scattered R values are not physiologically plausible. Consequently, we use an auto-regressive filter on the higher resolution modulation ratio reported from TFO to ensure that any new estimation for R has a memory factor stemmed from the previous estimations and update based on the current modulation ratio calculation. Fig. 5 demonstrates the auto-regressive filtering applied on the higher resolution modulation ratio measurements and the relationship between the filtered modulation ratios and the SaO_2 measurements taken in one round.

III. RESULTS

The assumption of linearity is important for the performance of the Linear Regression model. We employed linear regression to train on the subset of the data and evaluate the performance. In this direction, we used the scaled modulation ratio ($x = R$) as the feature and estimated the fetal oxygen saturation ($y = SpO_2$) as the dependant variable ($0 \leq y \leq 1$).

We observe that the function describing the relationship between the modulation ratio and the SpO_2 in (4) can be converted to one with a linear form, similar to (5) learning for $y' = 1/(y + k)$ instead of y . The value of k , which is a constant, is calculated based on molar extinction coefficients of wavelengths used. Considering the 850nm light as the λ_2 , and knowing that $\epsilon_{Hb}^{\lambda_2} = 691.32$ and $\epsilon_{HbO}^{\lambda_2} = 1058$ [14], the value of the constant k will be $k = -c(\epsilon^{\lambda_2}) = 1.885$. It is

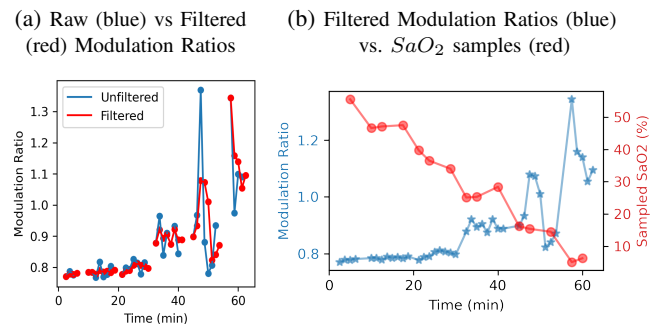


Fig. 5: Applying the auto-regressive (AR) filter on modulation ratios in this round

TABLE I: Performance of the proposed methods in estimation of fetal SpO_2 relative to fetal SaO_2 obtained from ABG samples

Estimation methods	Performance metrics	
	Correlation Factor (r)	MAE (%)
1: Extended windows	0.40	12.59
2: Overlapping windows	0.73	8.16
3: Physiologically Plausible	0.82	6.29

useful to note that k also acts as a regularizing term, and prevents y' reach indefinite values when $y \rightarrow 0$.

$$y'_i = \frac{1}{y_i + k} = w_0 + w_1 x_i \quad \forall i, i = 0, 1, \dots, n - 1 \quad (5)$$

We compared the performance of the methods on the full dataset of TFO data from both hypoxic rounds of the sheep experiment. The “leave one out” cross-validation mean absolute error score and Pearson’s correlation factor (r) are used to evaluate the performance of each method for estimation of fetal SpO_2 against the measured fetal SaO_2 .

Table 1 summarizes the performances of the three methods. Clearly, increasing the resolution of estimation from 10-minutes to 2.5-minutes has a significant impact on both performance metrics notably the improvement of 35% from the baseline of 12.59%. This is expected because 10 minutes is too long of a window for averaging. Over the course of 10 minutes, parameters such as fetal heart rate and SpO_2 are subject to change, and the estimator is afforded only one shot to make an estimation.

An improvement is also gained by considering physiological plausibility and the use of the auto-regressive filter, limiting the SpO_2 estimate variations within an acceptable margin from the previous readings, which will suppress the noise in the readings. This has improved the MAE furthermore by 23%. Fig. 6 illustrates the correlation between the estimated fetal SpO_2 and the actual fetal arterial blood oxygen saturation for the three approaches.

IV. DISCUSSION

In this work, we evaluated an algorithm and multiple approaches to estimate the fetal oxygen saturation during pregnancy on the data acquired by TFO from an at-term pregnant ewe in a hypoxic lamb model. We used a model to learn the relation of TFO estimations of fetal blood oxygen saturation (fetal SpO_2) with actual fetal arterial blood oxygen saturation (fetal SaO_2) and evaluated it on a sheep and found that the challenges we face can be handled using the notions of continuity and physiological plausibility.

Next, we wanted to account for the fact that we have some contributions from maternal tissue in the measured DC component in the power spectrum of the received light for both wavelengths, and we approximated the DC component from the fetal tissue by a scaling factor of the DC component of the received light. More importantly, this would make it possible for our algorithm to be evaluated on different systems. Scaling the DC component also acts as a normalization mean to account for various fetal depth and various fetal signal levels.

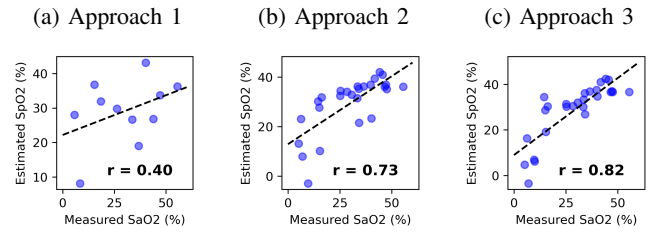


Fig. 6: Validation of estimated fetal SpO_2 values for the three proposed methods relative to the measured fetal SaO_2 s from ABGs

In summary, our approach to solving the problems of noisy and scarce readings and the difficulty of calibration is to use shorter time windows with overlapping and to utilize the physiological plausibility of the system. The method leverages the aforementioned notions to reduce measurement noise and improve calibration performance simultaneously. In this work, Cross-Validation of fetal SpO_2 estimates of the best approach had a correlation of $r = 0.82$ and the MAE of 6.29% with fetal SaO_2 . More complex models can be utilized to increase the generality of the algorithm on various systems in the future.

REFERENCES

- [1] D. D. Fong *et al.*, “Transabdominal fetal pulse oximetry: The case of fetal signal optimization,” *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)*, Oct 2017, pp. 1–6.
- [2] A. Zourabian *et al.*, “Trans-abdominal monitoring of fetal arterial blood oxygenation using pulse oximetry,” *Journal of Biomedical Optics*, vol. 5, no. 4, pp. 391–405, 2000.
- [3] D. D. Fong *et al.*, “Optode design space exploration for clinically-robust non-invasive fetal oximetry,” *ACM Transactions on Embedded Computing Systems*, vol. 18, no. 5s, 2019.
- [4] D. D. Fong *et al.*, “Contextually-aware fetal sensing in transabdominal fetal pulse oximetry,” in *Proc. 11th IEEE/ACM Conf. Cyber-Phys. Syst.*, 2020, pp. 119–128.
- [5] K. B. Gan *et al.*, *Adaptive Filtering Applications: Application of Adaptive Noise Cancellation in Transabdominal Fetal Heart Rate Detection Using Photoplethysmography*. Rijeka, Croatia: InTech, Jun. 2011, ch. 6.
- [6] D. D. Fong *et al.*, “Recovering the fetal signal in transabdominal fetal pulse oximetry,” *Smart Health*, vol. 9/10, pp. 23–36, 2018.
- [7] K. Vali *et al.*, “Non-invasive transabdominal assessment of In-Utero fetal oxygen saturation in a hypoxic lamb model,” *American Journal of Obstetrics & Gynecology*, vol. 224, no. 2, Supplement, p. S604, 2021.
- [8] D. D. Fong *et al.*, “Design and In Vivo Evaluation of a Non-invasive Transabdominal Fetal Pulse Oximeter,” *IEEE Transactions on Biomedical Engineering*, June 2020.
- [9] J. G. Webster, *Design of Pulse Oximeters*. Institute of Physics Publishing, 1997.
- [10] P. D. Mannheimer, “The light–tissue interaction of pulse oximetry,” *Anesthesia Analgesia*, vol. 105, no. 6, pp. S10–S17, 2007.
- [11] M. Nitzan *et al.*, “Pulse oximetry: Fundamentals and technology update,” *Medical Devices (Auckland, N.Z.)*, vol. 7, pp. 231–239, 2014.
- [12] E. D. Chan *et al.*, “Pulse oximetry: understanding its basic principles facilitates appreciation of its limitations,” *Respir Med*, vol. 107, no. 6, pp. 789–799, Jun 2013.
- [13] D. D. Fong *et al.*, “Validation of a novel transabdominal fetal oximeter in a hypoxic fetal lamb model,” *Reproductive Sciences*, June 2020.
- [14] S. L. Jacques, “Optical properties of biological tissues: A review,” *Phys. Medicine Biol.*, vol. 58, no. 11, p. R37, 2013.
- [15] P. D. Mannheimer *et al.*, “Wavelength selection for low-saturation pulse oximetry,” *IEEE Trans. Biomed. Eng.*, vol. 44, no. 3, pp. 148–158, Mar. 1997.