Dear BSN Technical Program Associates,

We would like to thank the reviewers for their constructive feedback on our submission. We have completely revised the paper to address the comments. The responses and associated revisions in the paper are detailed below.

Changes in the paper, relative to the original submission, are highlighted with blue font.

Reviewer 1:
The suggested method assumes that fetal heart rate is known by using the existing method such as cardiotocography. The authors do not describe how robust the suggested method is when there is error in the assumed fetal heart rate while the authors mentioned the problems of subjective interpretation of fetal heart rate patterns and the interobserver variability for the cardiotocography.

The existing modalities for sensing fetal heart rate (FHR), such as cardiotocography, are fairly accurate. The problem with the use of FHR for detection of babies at risk of birth asphyxia is not in inaccuracy of FHR sensing, but in the association between FHR patterns and the neonatal health outcomes. As a result, we did not consider the impact of error in reference FHR measurements on the proposed method. We acknowledge that such a consideration would enhance the scope of the study, and plan to address that as part of our future work.

When doing the 5-fold cross-validation, it's unclear whether there was data leakage between training and validation. In other words, it's unclear whether the same sheep's data was used for both training and validation.

Light propagation in pregnancy tissue, the phenomenon impacting the relationship between PPG signals and blood oxygen saturation, strongly depends on the measurement geometry, such as the tissue composition, fetal depth and concentration of different chromophores in the tissue. As a result, distribution of data collected from a subject is likely to be drastically different from another subject. In fact, transfer of learnings from a set of subjects to previously-unexamined subjects, as suggested by the reviewer, is an open problem in the context of Transabdominal Fetal Oximetry that is under active research. We should add that the issue is not prominent in classical finger pulse oximetry, given the relatively far smaller depth of the tissue under optical interrogation. We have made edits to clarify our setup, and highlight this point.

The suggested method was compared only against the other PPG-based method. It'd be beneficial to compare the suggested method against the traditional electronic fetal monitoring machines as well.

The aim of the proposed algorithm is to enhance extraction of the PPG signal, which is specific to light-based sensing, and does not exist in traditional approaches to fetal monitoring. As a result, our evaluation considers competing methods for extraction of fetal PPG. Evaluation of the impact on outcomes, where different approaches to fetal monitoring can be compared, is an ambitious objective that will require significant time and resources.

Reviewer 2:

My primary concern about this paper is the technical novelty. The authors claimed one of the contributions is the exploration of applying PSA to fetal signal recovery. However, prior works have already applied similar techniques (e.g., PRSA) to fetal signal detection/recovery. Lemay, Mathieu, et al. "Phase-rectified signal averaging used to estimate the dominant frequencies in ECG signals during atrial fibrillation." IEEE Transactions on Biomedical Engineering 55.11 (2008): 2538-2547. With that being said, the authors are suggested to conduct a more comprehensive literature review and clearly clarify their contributions.

Phase aligning indeed is not a new mathematical tool. However, the utility of the concept has not been explored in the context of the field and the type of signals (transabdominal light intensity data in pregnant subjects) reported in the paper . As is typical of many biomedical studies, novel aspects of the problem arise when specific requirements and subtleties of the target application are taken into consideration. For example, our proposed method aligns multiple pulses with a faint low-SNR fetal pulsation signal (typically -40db to -100db weaker than other contaminations due to superficial tissue) to obtain an average shape of the fetal PPG signal (oxygen saturation impacts light absorption of the blood, and thus, the shape, but not the dominant frequency of the fetal PPG).
and PSA is used to reinforce signal quality by trading off time resolution. In our case, the fetal heart rate is a known parameter and heavily used to assist the algorithm, while in application of PSA in other domains, such as the paper mentioned by the reviewer, extraction of the dominant frequencies is the objective .

We have revised the paper to better position the paper in the context of prior work, and to highlight the contributions of the paper.

Validating the efficacy of the proposed signal enhancement framework using a down-stream application (fSpO2 estimation) does not make sense to me. Since the fSpO2 estimation relies on a neural network, improvements in signal quality may not directly translate to a proportional increase in SpO2 accuracy. A more rigorous validation is the direct comparison of the enhanced signal with a ground-truth heartbeat waveform.

We acknowledge that the use of the down-stream test is not the ideal method to evaluate the performance of this new PSA method. However, the dataset utilized in the paper is collected in experiments with gold standard large animal models of pregnancy whose fetuses were

undergoing controlled desaturation. No contact-based fetal PPG was recorded during the experiments, no other reference measurement, other than $fSpO_2$, is available.
We also would like to stress that the amplitude of the PPG signal carries information about oxygen saturation, and that the PPG signal strongly depends on the measurement geometry. As a result, the inferred non-invasive PPG signals are expected to be different from the contact based PPG signals, though the morphology of the two signals should conceptually offer additional clues for validation.

We have made changes to the paper to highlight the discussion above. Thank you.

Reviewer 3:
It is not clear what other signal processing methods have been used to improve fSpO2 estimation from PPG data.
In this paper, the key proposed method is PSA. For completeness of the presentation, we have revised the paper to describe signal preprocessing steps (demodulation and filtering) that were used to generate the input data to the PSA algorithm. The output of the PSA algorithm is processed using a simple neural network model to infer $fSpO_2$, as described in the paper.

In the evaluation, it is not clear what is meant by the state of the art method [9] being used to generate fetal signal amplitudes as a baseline.

The state of the art method refers to synchronous detection, aka lock-in detection, using the reference FHR. It works by multiplying the input signal with a reference signal of the same frequency, a sinusoid with the same frequency as the FHR in this case, followed by low pass filtering of the result. This down-converts the desired signal to a low DC frequency while attenuating out-of-band noise and other frequencies.

We have revised the paper for clarification.

There is no information provided on how the fSpO2 data was estimated from the extracted fetal PPG data.

We take a supervised learning approach to estimation of $fSpO_2$ from multi-detector dual-wavelength PPG signals. We have revised the paper to describe the topic in more detail, subject to the limited page count of this paper, and have cited a reference that covers the topic in more depth.

Some of the logic (the goal was to extract fetal PPG, which can then be used to estimate fSpO2; there is already a ground-truth fetal heart rate extracted from a different sensor that can be used in the algorithm) were not well-laid out, and several readings were needed to fully understand how everything tied together.

Thank you for pointing this out. We have revised the paper for clarification.

PSAFE: Extraction of Faint Fetal PPG from Non-Invasively Acquired Mixed PPG Signals

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***Abstract*—Traditional approaches to intrapartum fetal monitoring, based on interpretation of fetal heart rate (FHR) tracings, have high false positive rates for detection of fetuses at risk of birth asphyxia. Transabdominal Fetal Pulse Oximetry (TFO) promises to supplement FHR trace interpretation through non-invasive sensing of fetal blood oxygen saturation ($fSpO_2$) from photoplethysmography (PPG) signals acquired through the maternal abdomen. However, the acquired signals, referred to as mixed PPG, contain contributions from both maternal superficial tissue layers and fetal tissue, as well as other noise sources. We propose Phase-Synchronized Averaging for Fetal Signal Enhancement (PSAFE), a novel algorithm that leverages fetal heart phase information to align and average mixed PPG segments. Evaluation using *in-vivo* data collected from pregnant ewe models demonstrate that PSAFE yielded a 43.4% reduction in mean absolute error, and a 25.9% improvement in correlation for $fSpO_2$ estimation, compared to a leading alternative approach.**

***Index Terms*—Fetal Photoplethysmography, Phase Synchronized Averaging, Transabdominal Fetal Pulse Oximetry**

I. Introduction

Electronic fetal monitoring (EFM), technically referred to as cardiotocography (CTG), is widely used for fetal health assessment during labor and delivery, where, the patterns in fetal heart rate (FHR) and uterine contraction tracings are interpreted by a trained provider to detect fetuses who are at risk of distress due to low oxygenation, and the associated brain injury. There is ample evidence that the approach has a high rate of false positives, and has likely contributed to the significant rise of intrapartum interventions, such as emergency Cesarean section deliveries [1], [2].

Transabdominal Fetal Pulse Oximetry (TFO), a novel technology for non-invasive and continuous sensing of fetal arterial blood oxygen saturation ($fSpO_2$), promises to address the limitation, via offering information about fetal access to oxygen, which has the potential to supplement the existing approaches to intrapartum fetal monitoring. Conceptually, TFO functions via processing of non-invasively captured mixed maternal-fetal photoplethysmography (PPG) waveforms to isolate faint fetal PPG signals, which can be subsequently analyzed to infer $fSpO_2$.

In this paper, we present PSAFE, a novel algorithm for extraction of fetal PPG from sensed mixed PPG signals, demonstrate its effectiveness using pregnant ewe models undergoing controlled fetal desaturation experiments.

II. Background

A. Transabdominal Fetal Pulse Oximetry (TFO)

A TFO device prototype is developed, which utilizes two Near-Infrared (NIR) LEDs (740 nm and 850 nm) and five photodetectors at different distances from the light sources to acquired mixed PPG signals (Fig. 1(b)) [3]. The radiated NIR photons may be scattered or absorbed by the molecules in the lightpath. In particular, the tissue is a highly scattering medium for NIR light, while oxygen saturation of blood impacts its NIR absorption. As shown in Fig. 1(a), the majority of sensed photons travel through, and thus interrogate, a banana-shaped pattern in tissue. [4].

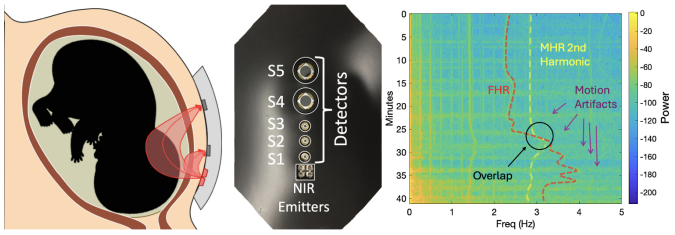

Fig. 1: (a) Conceptual view of Transabdominal Fetal Pulse Oximetry (TFO). (b) TFO Sensor Prototype [3]. (c) Spectrogram of Detected Signals

Non-invasive sensing of deep tissue faces challenges such as significant attenuation of radiated light, motion artifacts, and non-stationary signals, all of which degrade fetal signal quality and reliability. The radiated light exponentially attenuates with traveled distance in tissue, and given the typical depth of a fetus, the acquired mixed PPG signals contain very faint fetal PPG.

Figure 1(c) illustrates an example time-frequency spectrogram of the acquired mixed signal from a prenant ewe. Note that FHR may be overlapped with the second harmonic of the maternal cardiac cycle, or other noise artifacts. The in-band noise makes it challenging to accurately extract the fetal PPG signal amplitude using conventional signal filtering methods. Extraction of fetal PPG signal amplitude from the sensed mixed PPG signal is an essential precursor to estimation of $fSpO_2$, and is the objective of this paper. [5], [6].

B. Related Work and Contributions

Phase Synchronized Averaging (PSA) enhances periodic signals by aligning and averaging different periods of the signal, maintaining consistent features while attenuating inconsistent patterns and noise. [7]. PSA has been utilized in different biomedical application areas, ranging from determining the dominant frequency of atrial fibrillation [8] to estimation of fetal signal in synthetic datasets [9].

While the concept of periodic signal averaging is quite intuitive, its customization for enhancement of *in-vivo* mixed PPG signals, due to its unique application requirements, is fairly unexplored. In particular, this paper proposes a novel technique for accurate determination of signal period boundaries in the mixed PPG, when a reference FHR is available. The assumption is motivated by our intended clinical need in which, the TFO sensor is meant to supplement CTG-based intrapartum fetal monitoring, though which, reference FHR is readily available.

III. Proposed Method: PSAFE

We present PSAFE, a novel phase-synchronized averaging algorithm for extraction of faint fetal PPG signals. PSAFE consists of three steps. Phase estimation is performed to identify the periodic boundaries of each fetal cardiac cycle in the mixed PPG signal. Then, an alignment method is applied to extract such signal segments, and resample them to the same number of samples. Finally, the aligned signals are averaged to estimate the amplitude of the fetal PPG signals.

A. Phase Estimation

Phase estimation is performed to mark the start and end points of each fetal cardiac cycle. As the intention is to use TFO to supplement existing intrapartum fetal monitors, such as CTG, which reliably measure FHR, we assume that the FHR data is available. Note that FHR refers to average number of heart beats over a time period, and thus, it does not readily yield accurate boundaries of one cardiac cycle (beat to beat variation).

A convolution algorithm is used to detect the phase of fetal heart rate. First, a limited-length convolution kernel is generated based on the sample rate of the data along with the known FHR. Let us set L to be kernel length, f to be target frequency for kernel (FHR), and f_s to be sampling frequency for the data stream. $Sine$ shape is used to match the target frequencies, and $Gaussian$ is a mask that ensures the $kernel$ places more weight near the center ($\mu = 0$), and a decreasing weight as it reaches the boundaries.

$$kernel[i_n] = Sine[2\pi f \frac{i_n}{f_s}] \times Gaussian[i_n, \mu, \sigma] \quad (1)$$

$$i_n = -\frac{L-1}{2} + n, \text{ where } n = 0, 1, 2, ..., L-1 \quad (2)$$

In equation(1) we can observe that $Sine$ is an odd function, while $Gaussian$ is a even function. Consequently, when the kernel is applied to a symmetric input series i_n, the resulting sum will be zero. Therefore, the kernel always forms a zero-sum series, which ensures that no DC shift is introduced during the convolution process.

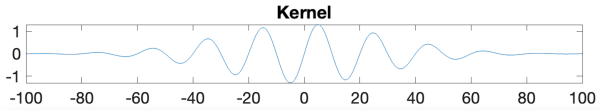

Fig. 2: Graphical representation of the convolution kernel used for phase detection.

Fig.2 shows an example in which the kernel is generated with a $L = 201, \mu = 0, \sigma = 0.3$, a target frequency $f = 4Hz$, and a sampling frequency $f_s = 80Hz$.

Let $A = a_0, a_1, a_2, a_3, ...$ be the data stream. The convolution kernel is then applied to the data stream to detect the phase of the fetal heart rate.

$$ConvolutionResult(i) = A * kernel \quad (3)$$

The local peak of $ConvolutionResult$ will be considered as the boundaries (starting and ending point) of the signal for a specific frequency for which the $kernel$ is generated.

An example is shown in Fig. 3: a mixed signal with target signal at $f_s = 4Hz$, and two noise signals at $f_{n1} = 7Hz, f_{n2} = 13Hz$, both at half amplitude compared to the target signal. The sampling frequency, $f_s = 80Hz$, with a time from $t = 0$ to $t = 4$. The $kernel$ used in this computation is the same as that illustrated in Fig.2. The dashed vertical black line is the index where the peaks are detected by the convolution computation.

$$Signal(t) = sine(f_s, t) \quad (4)$$

$$Noise(t) = 0.5(sine(f_{n1}, t) + sine(f_{n2}, t)) \quad (5)$$

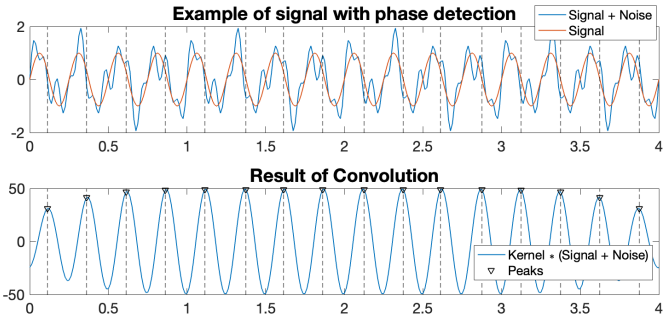

Fig. 3: Example of convolution-based phase extraction

B. Relation to Short Time Fourier Transform and Wavelet

In PSAFE, the convolution kernel fundamentally differs from the STFT and Wavelet Transform. Unlike STFT, which relies on a fixed basis set determined by window length, PSAFE employs an over-complete set of bases with arbitrary frequencies to best match the fetal signal, enabling high sensitivity within short windows. While not reversible, this is inconsequential since the kernel serves only to estimate phase. Similarly, unlike Wavelets, PSAFE uses fixed-length

kernels and does not perform time–frequency decomposition. Both STFT and Wavelets transform signals into the frequency domain, whereas PSAFE extracts phase information directly in the time domain. Moreover, PSAFE kernels are not limited to sinusoids and can adopt waveform shapes tailored to heartbeat detection, improving sensitivity to fetal PPG morphology.

C. Signal Chopping, Outlier Rejection and Alignment

Based on phase information, continuous signals will be chopped into segments associated with individual fetal heartbeats. Since fetal heartbeats may vary in length, the chopped signals will not have identical length. However, the average length can be estimated based on the target frequency (FHR) and the sampling frequency. An outlier rejection step is used to discard signals whose length significantly deviates from the expected length. Subsequently, the chopped segments are resampled to have a uniform length across beats.

Fig. 4 shows a set of aligned, chopped signal segments from the running example. The averaged signal has reduced noise, and an amplitude of 1 for the signal is recovered, matching the original signal (orange) shown in Fig. 3.

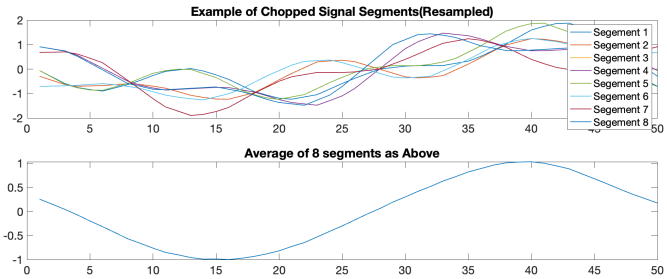

Fig. 4: Example of Signal Segment Averaging

D. Non-Stationary Target Signal

In real-world signals, the target frequency is not constant, as the fetal heart rate may vary over time. To address this variability, the data is divided into one-second intervals during which, the target frequency is assumed to remain constant. Thus, the kernel re-examined and potentially updated every second to match FHR.

To compute the amplitude of fetal PPG at time t, all segments within a 60-second window centered at t are averaged. The output will have a resolution of 1 Hz.

IV. Evaluation

A set of data acquired in pregnant ovine models undergoing controlled fetal desaturation was utilized to evaluate the PSAFE method. The dataset contains approximately 24,000 seconds of data collected from 8 ewes. As no ground truth for fetal PPG amplitude is available, $fSpO_2$ estimation is used as a downstream task to evaluate PSAFE. In this case, estimated $fSpO_2$ is compared against reference values obtained via blood gas analysis during the experiment.

A well-established competitor is used to as a baseline for comparison against PSAFE [10]. This State of the Art method uses synchronous (lock-in) detection [10], [11] to estimate fetal PPG amplitude from the sensed mixed PPGs.

A. Data Collection

The data was collected from pregnant ewes, where the TFO device was placed on the maternal abdomen to acquire mixed PPG signals. (Fig. 5) [12]. Blood gas was drawn from the instrumented fetus to obtain reference fetal blood oxygen saturation values ($fSaO_2$). Additional measurement devices were used during the experiment to record other physiological data, including maternal and fetal heart rate.

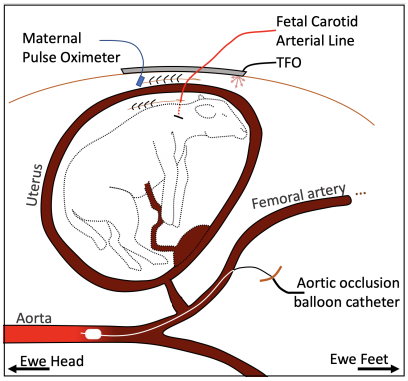

Fig. 5: Data Collection in Pregnant Ewe Model [12]

B. Alternative Method

The State of the Art method for amplitude estimation for a signal of known frequency is based on synchronous (lock-in) detection, which operates by multiplying the mixed PPG signals with a sinusoid at the reference (FHR) frequency, extracting the signal component at the frequency of FHR [10].

C. Preprocessing and Feature Extraction

To estimate $fSpO_2$, AC amplitude of fetal signal and DC amplitude are required for both 740 nm and 850 nm wavelengths [6]. Each of the 5 photo-detectors senses a different PPG given the varying distance to the light source [5], [12]. Each light sources is toggled on and off a different rate, and the raw signal is extracted via frequency demodulation, followed by low pass filtering. Either PSAFE or the alternative method are utilized to compute 10 channels of AC/DC features.

A simple neural network is used to estimate $fSpO_2$ from the feature vectors [10]. The neural network consists of 4 layers: 1 input layer, 2 hidden layers, and 1 output layer. The input layer takes fetal signal amplitudes. The output layer predicts $fSpO_2$ values.

Given that validation of TFO on a previously unexamined subject is an open problem in its own right, a 5-fold cross-validation approach was employed, in which the data from each sheep was divided into five equal-length disjoint sections.Four sections are added to the training set, while the remaining section is included in the training set. This process is repeated five times with fresh trainings, ensuring that each section is used as a validation set exactly once. This approach

ensures robustness and reduces the risk of overfitting by testing the model on unseen data during each fold [13]. The (MAE) is calculated for each fold, and the average MAE across all folds is used as the evaluation metric.

D. Result

To evaluate the PSAFE method, 100 random seeds were used to assess the stability and performance of the approach against the existing lock-in detection [10]. As shown in Table I, PSAFE demonstrated significant improvements over the leading competitor, achieving a lower mean absolute error (MAE) and higher Pearson's correlation coefficient, highlighting its effectiveness in enhancing fetal signal extraction and $fSpO_2$ estimation accuracy.

TABLE I: Comparison of methods for $fSpO_2$ estimation

Method	Mean Absolute Error			Standard Deviation	Pearson's r Correlation
	Mean	Best	Worst		
lock-in detection [10]	6.97	5.85	8.35	6.22	0.694
PSAFE	3.94	3.37	4.92	4.10	0.874
improvement	43.4%	42.3%	41.0%	34.0%	25.9%

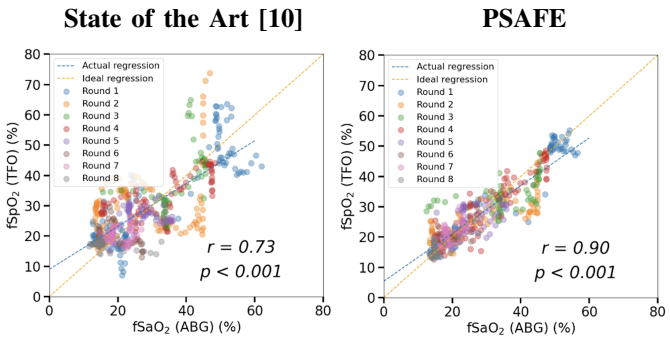

Fig. 6: The impact of PSAFE vs. lock-in detection [10] on the accuracy of $fSpO_2$ estimation. The plot shows the distribution of errors for an average random seed.

The proposed method demonstrates potential for advancing TFO, and improving the accuracy of non-invasive $fSpO_2$ sensing. The current approach to phase detection relies on mixed PPG signal itself, which may fail when the fetal signal is too weak. The phase detection step may be further enhanced by incorporating an electrocardiogram (ECG) sensor, which is expected to offer a more robust and reliable marker of individual fetal heart beats. This capability opens up new possibilities for non-invasive fetal monitoring, enabling the detection of faint PPG signals in challenging noise environments, and promising to significantly improve the accuracy and reliability of non-invasive $fSpO_2$ measurement.

V. Conclusion

This paper introduced PSAFE, a phase-synchronized averaging algorithm designed to enhance faint fetal photoplethysmography (PPG) signals for improved estimation of fetal arterial blood oxygen saturation ($fSpO_2$). By aligning PPG waveforms based on individual fetal heart beats, and averaging across cycles, PSAFE effectively suppresses noise and improves signal quality. Evaluation on *in-vivo* data demonstrated a substantial performance gain over a leading alternative method, achieving a 43.4% reduction in mean absolute error and a 25.9% improvement in correlation, in reference to the ground truth values obtained via blood gases. These results highlight PSAFE's potential for advancing non-invasive fetal monitoring. Future work will explore integrating fetal ECG for more robust phase detection, generalization to previously unseen subjects, and validation of the method in human subjects.

VI. Acknowledgments

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