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 40.0% reduction in mean absolute error, and a 22.6% 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].

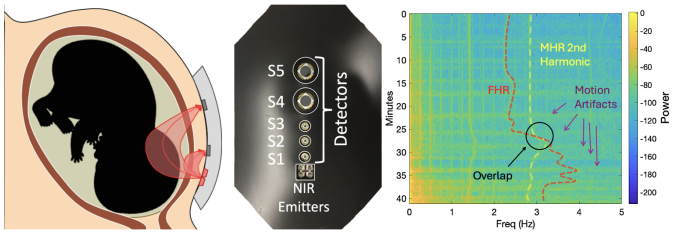

Fig. 1: (a) Conceptual view of Transabdominal Fetal Pulse Oximetry (TFO). (b) TFO Sensor Prototype [3]. (c) Spectrogram of Detected Signals

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.

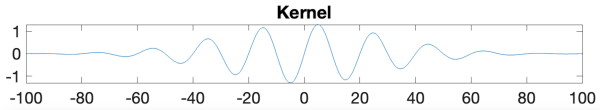

Fig. 2: Graphical representation of the convolution kernel used for phase detection.

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.

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

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

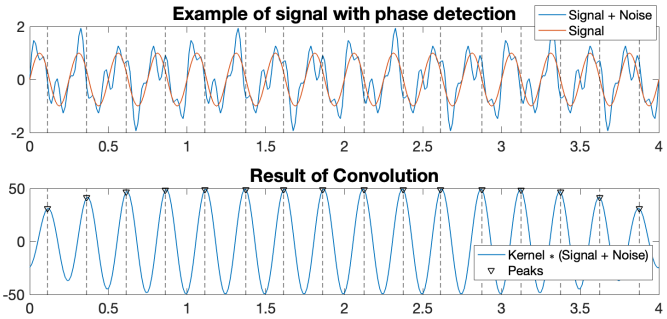

Fig. 3: Example of convolution-based phase extraction

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.

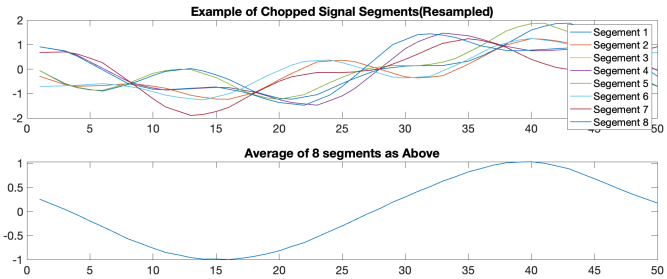

Fig. 4: Example of Signal Segment Averaging

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.

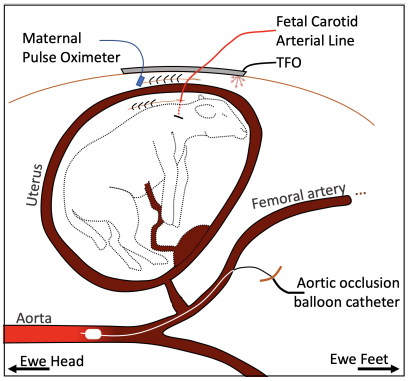

Fig. 5: Data Collection in Pregnant Ewe Model [12]

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	0.69
PSAFE	4.18	3.42	4.73	4.51	0.85
improvement	40.0%	38.7%	43.4%	27.5%	22.6%

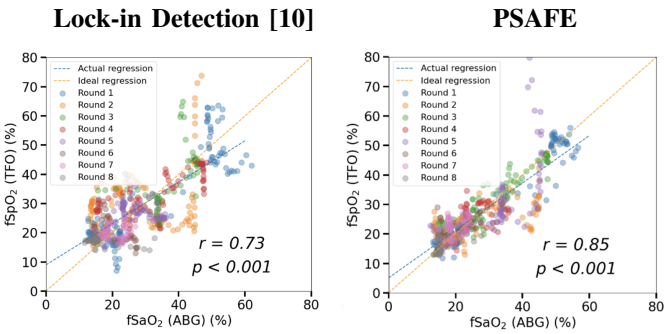

Fig. 6: The impact of PSAFE vs. lock-in detection [10] on the accuracy of $fSpO_2$ estimation. The plot shows the distribution of errors for an average random seed.

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 40.0% reduction in mean absolute error and a 22.6% 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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