Inverse Modeling Approach for Fetal Oxygen Saturation Estimation with Spatial Intensity

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Abstract: Non-invasive fetal saturation prediction is challenging. We propose a multi-detector, inverse modeling, ML based approach. Trained on a large simulated simple tissue model dataset, our generalized NN can estimate simulation parameters given the simulation results. Our model achieves a 9.2% overall validation MSE for tissue model parameters.

1. Significance

Fetal Pulse oximetry (PO) systems estimate the prenatal arterial oxygen saturation (SaO2) using the principles of near-infrared spectroscopy. This involves shining light within the patient's body and capturing the modulated information in the reflected light. One such class of PO systems relies on continuous spatial intensity (SI) measurements from multiple detectors at different distances from a pulsating light source. Any analytical approach to convert intensity to fetal SaO2 requires knowing patient body-geometry specific terms. Conventional finger PO bypasses this by utilizing calibration data from adult volunteers. However, fetal PO systems operate with a substantially different geometric setup, and with disparate saturation ranges compared to adults. There remains a research gap in developing more accurate fetal PO approaches which is essential for ensuring better prenatal health monitoring.

2. Aim

We approached the problem from an inverse modeling angle. Instead of focusing on just fetal saturation, we took a more holistic approach. We simulated a double-body, flat tissue model under different sets of conditions, dubbed tissue model parameters (TMPs). For now, we deal with 5 TMPs: Maternal/Fetal Hemoglobin (Hb) Saturation and concentration, and Fetal depth. Then, our goal is to create a robust model for estimating all TMPs from the simulated SI.

3. Method

3.1. Simulation Setup

We used a flat, four-layered, homogenous, double-body tissue model for this study [1]. We simulate two different wavelengths, 735nm, and 850nm, with different sets of optical properties [2], [1], using a GPU-based Voxel Monte-Carlo (MC) simulator, MCXtreme [3]. Our light source is a single Gaussian beam of 5mm waist radius and multiple detectors placed in concentric circles. The intensity is averaged over each circle.

We vary the absorption coefficient (μ_a) of the Maternal Wall(Layer 1) and Fetal Tissue Layer(Layer 4) based on the first 4 tissue model parameters: maternal and fetal Hb saturation/concentration respectively. The rest of the optical properties remain unchanged. The fifth tissue model parameter, maternal wall thickness, affects the tissue geometry. For each case, we store the optical path data per simulated photon. This setup allows us to run simulations once per model geometry/wavelength and efficiently calculate the intensities in post-processing.

We vary the TMP in discrete levels. We vary maternal & fetal saturations from 90% to 100% and 10% to 60% respectively in 5 levels. The Hb concentration for maternal wall & fetal layer is varied from 11 to 15 g/dL and 0.10 to 0.16g/dL respectively with 5 levels [4]. Additionally, we also simulate Hb concentration values 5% above and below these levels for both layers. This helps us simulate pulsation peaks. The maternal wall thickness is varied from 6mm to 16mm with 2mm resolution.

3.2. Data Preprocessing

We perform three steps of preprocessing: interpolation, normalization, and combining data pairs. MC convergence noise persists within the far detectors of the simulation data despite averaging a set of detectors in circles. We

replace the simulation data with a piece-wise weighted linear regression on the log of the SI. The features are normalized per-detector to have zero mean, unit variance. To emulate pulsation on a static simulation, we pass 2 data points with fetal Hb concentration within 5% range of each other. For each pair, the other TMPs remain constant.

3.3. Machine Learning Model

We use a 4-layered perceptron with batch normalization & dropout and ReLU non-linear activation. The model input is 80-dimensional(20 detectors $\times$ 2 wavelengths $\times$ 2 data points) and produces a 6-dimensional vector. The output includes all 5 TMPs, with two different labels for the two fetal Hb concentration levels.

3.4. Performance Evaluation

Generalizing fetal saturation estimation across different patients has always been a major issue with PO techniques. This led us to adopt a held-one-out style validation strategy. During training, all simulation data from one specific fetal depth is held out.

4. Results

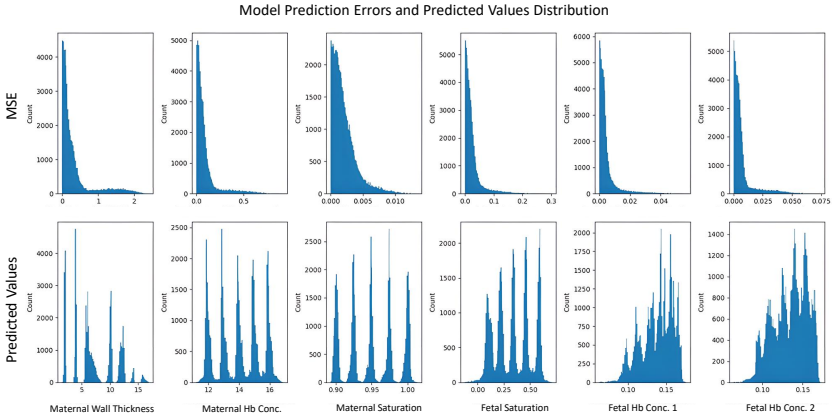

Fig. 1. The performance of our trained model is illustrated in terms of both the MSE distribution produced for each of the 6 TMPs in the simulation as well as the distribution of the predicted values. Due to our discrete simulation space, the predicted value distribution demonstrates spikes centering around the discretization points

Our model reaches a 9.2% validation MSE on all 6 TMPs combined, with a comparable training error. In terms of estimating saturation, 90% of the error distribution falls below 7.5% in absolute saturation error.

5. Conclusion

We were able to produce more robust results by factoring in all the TMPs within our model compared to only estimating fetal saturation. In other words, common important features exist between the different TMPs which can better guide the model optimization process compared to a targeting single label.

References

1. D. D. Fong, K. Vali, and S. Ghiasi, "Contextually-aware fetal sensing in transabdominal fetal pulse oximetry," in *2020 ACM/IEEE 11th International Conference on Cyber-Physical Systems (ICCPS),* (IEEE, Sydney, Australia, 2020), pp. 119–128.
2. P. Mannheimer, J. Cascini, M. Fein, and S. Nierlich, "Wavelength selection for low-saturation pulse oximetry," IEEE Trans. on Biomed. Eng. **44**, 148–158 (1997).
3. "Monte Carlo eXtreme (MCX) - CUDA Edition," Monte Carlo eXtreme (2021).
4. N. Bosschaart, G. J. Edelman, M. C. G. Aalders, T. G. van Leeuwen, and D. J. Faber, "A literature review and novel theoretical approach on the optical properties of whole blood," Lasers Med. Sci. **29**, 453–479 (2014).