Robust Modelling of Reflectance Pulse Oximetry for SpO$_2$ Estimation

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Abstract—Continuous monitoring of blood oxygen saturation levels is vital for patients with pulmonary disorders. Traditionally, SpO$_2$ monitoring has been carried out using transmittance pulse oximeters due to its dependability. However, SpO$_2$ measurement from transmittance pulse oximeters is limited to peripheral regions. This becomes a disadvantage at very low temperatures as blood perfusion to the peripherals decreases. On the other hand, reflectance pulse oximeters can be used at various sites like finger, wrist, chest and forehead. Additionally, reflectance pulse oximeters can be scaled down to affordable patches that do not interfere with the user’s diurnal activities. However, accurate SpO$_2$ estimation from reflectance pulse oximeters is challenging due to its patient dependent, subjective nature of measurement. Recently, a Machine Learning (ML) method was used to model reflectance waveforms onto SpO$_2$ obtained from transmittance waveforms. However, the generalizability of the model to new patients was not tested. In light of this, the current work implemented multiple ML based approaches which were subsequently found to be incapable of generalizing to new patients. Furthermore, a minimally calibrated data driven approach was utilized in order to obtain SpO$_2$ from reflectance PPG waveforms. The proposed solution produces an average mean absolute error of 1.81\% on unseen patients which is well within the clinically permissible error of 2\%. Two statistical tests were conducted to establish the effectiveness of the proposed method.

Clinical relevance The proposed method ameliorates our current understanding of reflectance based pulse oximetry and provides a method to estimate SpO$_2$ from reflectance pulse oximeters.

I. INTRODUCTION

Pulse oximetry is a non intrusive method used to measure the amount of oxygen saturation in a persons blood. Peripheral Capillary Oxygen Saturation (SpO$_2$), an estimate of the amount of oxygen in the blood, is conventionally obtained by taking the ratio of volume of oxygenated haemoglobin to that of the total haemoglobin. This is estimated by passing light of two different wavelengths, generally Red (660 nm) and Infrared (IR)(890 nm), and analyzing the amount of light absorbed along the way [1]. This provides information about the pulsatile arterial blood flow.

The most prevalent type of pulse oximetry is transmittance pulse oximetry, wherein the light passes through the region of interest (traditionally the finger) and the required analysis is carried out. A relatively unconventional method is reflectance pulse oximetry [2], in which the intensity of the reflected light is analysed. Under a controlled clinical environment as

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described in Pälve et al. [3] and König et al. [4], the need and success of reflectance pulse oximetry over transmittance is well established.

Despite its clinical necessity, estimation of SpO$_2$ from a reflectance photoplethysmogram requires a novel approach due to the inherent path difference between the red and IR wavelengths at the receiver. The variation in this path difference is not constant and depends upon the nature of one’s skin and tissue[5]. This invalidates the use of one-time calibration as done in transmittance pulse oximeters. As a result, a novel data driven approach to model reflectance pulse oximetry, subsequently estimating SpO$_2$, would enable a flexible yet robust approach that circumvents the current problems experienced by reflectance pulse oximetry.

Venkat et al. [6] proposed a calibration-less Machine Learning (ML) approach to derive SpO$_2$ from reflectance PPG waveforms. However, the number of data points corresponding to each SpO$_2$ value obtained for the study is skewed in the favour of higher SpO$_2$ values, implying that the algorithm was not tested across all possible SpO$_2$ values. Furthermore, the proposed methodology was not tested on new patients. In order to arrive at a generalizable decision system centered around deriving SpO$_2$ from reflectance pulse oximetry, our contributions are as follows:

1) We identified a data acquisition protocol that aims to acquire a wider range of values of SpO$_2$ from the same patient in order to understand the variation of reflectance PPG waveform with SpO$_2$.

2) We perform a comprehensive analysis on the data acquired and corroborate the requirement of a data-driven approach.

3) We examine previous ML methods and demonstrate its ineffectiveness in generalizing to unseen data.

4) We propose a method of estimation, requiring minimal calibration, that would generalize well to new patients. We quantify the estimation using Box plots and Bland Altman analysis.

II. DESIGN METHODOLOGY

A. Data Acquisition Protocol

A clinical study was conducted to analyze the feasibility of estimating reflectance SpO$_2$ measurements from transmittance SpO$_2$. The hardware design used for all the experiments in the proposed method was the same as that used in Venkat et al. [6]. The device information, clinical protocols, and the study objectives were approved by the Institutional Review Board, Christian Medical College and Hospital (CMC), Vellore. Data was collected with informed
consent from 28 subjects, suffering from various pulmonary disorders, with natural SpO₂ levels without external aid varying from 60% to 100%. Reflectance probes were attached to the subject in the following locations: finger, wrist and forehead. Nellcor transmitance probe, which was used to obtain reference SpO₂, was attached to the finger (same hand) when the data was collected. Arterial Blood Gas (ABG) test [7] was done on the subject, in parallel, to measure their SaO₂. Prior to the ABG test, oxygen mask was removed from the subject to measure their natural SpO₂ level. This period would correspond to a drop in the SpO₂ levels of the patient. Once the ABG test was conducted, the supplemental oxygen supply was resumed which led to an increase in SpO₂ levels. Note that the data collection (shown in Figure 1) was initiated a few minutes before the ABG test was conducted and was concluded a few minutes after the test. To the best of our knowledge, this is the first procedure in which a continuous wide range of SpO₂ values were obtained for a single patient.

B. Data Preprocessing

The transmittance and reflectance SpO₂ obtained from the fingers with a sampling frequency of 600 Hz were preprocessed in a similar fashion. These steps are elucidated below:

1) **Moving Average (MAV) Filter**: The Red and IR signals were passed through a MAV filter with a window length of 50 samples to smoothen them, thus removing high frequency noise components.

2) **Detrending**: Since both the red and IR signals had exhibited baseline wander, detrending was carried out to ease the process of peak and valley detection.

3) **Peak and valley Detection**: Position of peaks and valleys were extracted from the detrended signals. Subsequently, erroneous peaks and valleys were discarded based on the average peak-to-peak and valley-to-valley distance.

4) **Signal Quality Check**: The signals were deemed fit based on the cross correlation between the red and IR signals.

The length of the window and the percentage overlap was empirically chosen to be 4 seconds and 25% respectively. This was decided based on the average change in the DC value within a window.

C. Problem Formulation

From each window in the transmittance waveform, a ratio was obtained by combining AC and DC components of both wavelengths, using the following formula

\[
R_{\text{value}} = \frac{(\text{RED}_{AC}/\text{RED}_{DC})}{(\text{IR}_{AC}/\text{IR}_{DC})}
\]

The actual SpO₂ was obtained from the \( R_{\text{value}} \), which is the standard method for SpO₂ estimation. The goal of the proposed method is to estimate the SpO₂ value by modelling the relationship between the reflectance PPG waveform and the transmittance SpO₂.

D. Exploratory Data Analysis (EDA)

Although the data acquisition obtained a wide range of SpO₂ values across various patients, it is clear from Figure 2 that this approach does not reduce the massive imbalance against the lower values (<75%) of SpO₂. This was expected as it is prohibitively hard to allow a patient to have a low SpO₂ level for longer periods.

Furthermore, a linear relationship between \( R_{\text{value}} \), calculated from the reflectance signal (reflectance-\( R_{\text{value}} \)), and the corresponding SpO₂, obtained from the transmittance signal (transmittance-SpO₂), was observed for individual patients as shown in Figure 3. For each individual a unique straight line was obtained. Examples of this trend is shown on three patients who were randomly picked. However, there were two patients whose \( R_{\text{value}} \)-SpO₂ relationship deviated from the observation above. On closer examination of their PPG waveform, it was inferred that different reflectance-\( R_{\text{values}} \) were getting mapped to the same transmittance-SpO₂ values. The reason for the same is discussed in Section [IV].

III. EXPERIMENTS AND RESULTS

A. Examination of previous machine learning methods

Venkat et al. [6] proposed to model reflectance pulse oximetry by using a classifier wherein each target class corresponds to a rounded off SpO₂ value. The data representing each SpO₂ class was split into a train-validation

† code is available at https://github.com/prithusuresh/Reflectance-SPO2
set of 70%-30%, which was later accumulated. This was done to tackle the severe imbalance in the representation of lower SpO₂ values. Venkat et al. showed that the bagging of decision trees provides the best accuracy across different values of SpO₂. In order to test the ability of these models to generalize, the current work splits the data into three sets namely, train, validation and test sets. To deal with the imbalance, majority undersampling was utilized. Data obtained from 20 patients was split randomly into 10 folds of train and validation. Data from the rest of the patients was put into a test set. Both bagging (Random Forest Classifier and Random Forest Regressor) and boosting (Gradient boosting) were tried. Multiple features as given in Venkat et al. [6] were extracted from the transmittance waveform. The reported evaluation metrics are Average Mean Square Error (Avg MSE), Average Mean Absolute Error (Avg MAE) and the Average R² Score (Avg R² Score) across the validation and test set. Table I highlights the performance of multiple machine learning models on the validation set. Table II highlights the performance of all these models on the test set.

### B. Proposed Estimation Method

As the transmittance-SpO₂ vary linearly with the reflectance-\(R_{value}\) (corroborated in Figure 5), we use a straight line to model the relationship between transmittance-SpO₂ and reflectance-\(R_{value}\). Given a new patient, whose reflectance-\(R_{value}\) and transmittance-SpO₂ are known, the objective is now reduced to finding the best fit line. The training set was computed from the data of those patients (\(\Pi\)), whose SpO₂ values varied over a range greater than 15, which totalled to 10 patients. The training set (\(\tau\)) consists of individual straight lines (\(l_i\)) that best captured their respective reflectance-\(R_{value}\) and transmittance-SpO₂ relationship. Thus,

\[
\tau = \{l_i\} \forall i \in \Pi
\]

The calibration set (\(\gamma\)) consists of five values of reflectance-\(R_{value}\) and transmittance-SpO₂ pairs. The number of points chosen in the calibration set is a trade-off between an accurate representation of the new patient versus the calibration time. All these five points were values obtained between 90-95, as these are better represented in our dataset Figure 2. The lateral distance (LD), defined as the absolute difference in \(R_{value}\) between each point in the \(\gamma\) and each line in \(\tau\) for the corresponding SpO₂, is computed. A point is matched to a line in \(\tau\) if it has the least LD. The line \(l_i\), with the most number of matches, is selected to model the new patient. Table III highlights the results obtained using the proposed decision system on twelve unseen patients. Only these patients exhibited a SpO₂ range over 10%. The other 6 patients displayed an inadequate range and were not considered.

### IV. Discussion

From Table II, it is observed that the ML methods do well on the validation set. This implies that the model seems to be performing well on the unseen SpO₂ values of the same patient. However, Table II shows that the ML models do not generalize well to the test set. The poor performance of these models can be explained by the inherent difference in the distribution of the data. The path difference occurs as a result of the features that were used were not discriminative of the path length in different people.

Table III demonstrates the effectiveness of the proposed method on the test set. The Mean Absolute Error (MAE) is
computed for all the patients on the test set. The Average of the MAE across all patients is 1.81%. This significantly outperforms the best ML model which gave an Average MAE of 4.490. However, for certain patients it was observed that the MAE values were as high as 3.18. On closer analysis, it was observed that this was due to predictions on certain windows being highly erroneous, resulting in a skewed average value. This aberration is a result of abnormal R_value computation due to a high DC component of the red wavelength. The high DC component caused multiple reflectance-R_values to be mapped to the same SpO2 values, as observed in section II-D. This observation can be corroborated by the box plot shown in Figure 4. It can be seen that the 75% quartile range lies within 2% for all except one patient. The few outliers had produced a large error thus increasing the average of the MAE. However, the box plot does not take into account the possibility of systematic and random errors or bias in the measurement and computation of SpO2 from the transmittance PPG waveform.

A better understanding about the degree of agreement between the estimated SpO2 and the actual SpO2 that accounts for the errors in measurement of SpO2 is given by the Bland-Altman analysis. To this end, the Bland-Altman plots for four patients are shown in Figure 5. The Limits of Agreement (LoA) were defined as ±1.96SD of the mean difference. Generally, it is recommended that the accurately predicted observations lie within the error band of ±2%. Figure 5a and 5b show examples where the LoA is well within the error band indicating good estimations of SpO2. It is also clear that more than 95% of the points are within the LoA. These plots are representative of 83% of the patients. For two patients, due to the presence of large outliers, the LoA marginally eclipses the error band as shown in Figure 5c and 5d. Given more training data that covers a larger distribution and a robust preprocessing stage to discard signals with abnormally high values of DC amplitudes, the proposed method is likely to generalize even better to unseen data. Nevertheless, it provides a massive improvement over ML based methods across all patients.

V. CONCLUSIONS

This work proposes a novel method for estimating SpO2 from reflectance pulse oximetry with minimal calibration using SpO2 obtained from transmittance PPG signals. However, subsequent statistical analysis showed that the modelling could be improved with more data and better selectivity.

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