Analysis of Pulse Oximetry Signals through Statistical Signal Processing Techniques

Byungsool Moon

Biomedical Signal Processing Laboratory, Portland State University

***Abstract*—Signal processing techniques for Pulse Oximetry can typically be applied to estimate the oxygen saturation in the time and frequency domain. This paper describes whether or not Pulse Oximetry signals are consistent to calculate oxygen saturation for different level of measurements through the three patients' data. This is accomplished using the statistical signal processing techniques; Autocorrelation Function (ACF), Crosscorrelation Function (CCF), Power Spectral Density (PSD), and Coherency. We can confirm the consistent patterns of Pulse Oximetry signals from the limited experiment and see the fact that Pulse Oximetry may not be calibrated correctly or even fail to read the oxygen saturation.**

***Index Terms*—Pulse Oximetry, R value, Oxygen Saturation (SpO_2), Autocorrelation Function (ACF), Crosscorrelation Function (CCF), Power Spectral Density (PSD), Coherency**

I. Introduction

Pulse Oximetry estimates arterial hemoglobin oxygen saturation using analysis of light waveforms through a capillary tissue bed. The measurement of the oxygen saturation (percent) in hemoglobin has become a standard in operating rooms, critical care units, and emergency health care [1]. However, its usage in other areas is limited because of some limitations such as motion artifact and low perfusion. Many research papers have addressed the issue of the disadvantages and introduced new algorithm to overcome these limitations. Especially, due to low blood flow the low perfusion is a major contributor to the high rate of false alarms in pulse oximeter [2]. An interesting phenomenon that we found was that the shape and strength of oximetry signal changes significantly with different height of the measurements compared to patient's heart level. The measurement point used in this experiment was finger tip of patient and two extreme levels of measurement were chosen; High Level Measurement (HLM) and Low Level Measurement (LLM). The HLM represents that the patient with elevated hands and the BLM patients with lowered down hands.

Pulse Oximetry is a pulse dependent technique and current pulse oximeters use a weighted moving average algorithm to calculate the oxygen saturation (SpO_2) values using Photoplethysmograpic (PPG) red and infrared signals. If we know R value (the ratio of ac and dc component for each red and infrared signals), a direct conversion from the R value to SpO2 is possible due to empirical calibration curve.

Autocorrelation function (ACF) and Crosscorrelation function (CCF) are estimated to show self correlation and joint similarity of red and infrared signals with the time lag. Power Spectral Density (PSD) and Coherency are also estimated in order to see the frequency characteristics and correlation of signals at each frequency.

This paper is focused on finding common and different features of pulse oximetry signals among the patients and between different height measurements using ACF and PSD. Additionally we search for the relationship between red and infrared signals for each patient using CCF and Coherency. The significance of this paper is the evaluation of whether or not Pulse Oximetry signals are consistent to calculate oxygen saturation for different levels of measurements from the patients' data.

II. Methodology

A. Data Acquisition

Pulse oximetry circuit was directly built to measure the data, rather than using a commercial oximetry device. The data was collected and digitized by National Instrument Data Acquisition system with 100k Hz sampling frequency. Three healthy volunteers were studied at the Biomedical Signal Processing Laboratory, Portland State University. Each red and infrared signal was sampled at 400Hz for 30 second periods.

B. Analysis of Oximetry Signals

Pulse oximetry signal is known to vary from the patient to patient and even from measuring site to site. The average and correlation of signal are not independent of time, which means the signal is not stationary and ergodic. However, to apply the relevant statistical signal processing techniques it was assumed that the measured time series data were locally stationary in a wide sense.

Correlation functions were estimated to measure the similarity of signals. ACF was used to measure the self-similarity of each signal and CCF was employed to show the correlation between red and infrared signals. The biased estimator which has smaller mean square error (MSE) and less variability than an unbiased estimator was used to estimate the ACF and CCF. These were normalized and the maximum lag was 30 sec. CCF can be only applied to real-time measured data, so we focused on red and infrared signals for joint signal analysis.

PSD was used to show frequency characteristics and the distribution of signal power in the frequency domain. Before estimating the PSD, we subtract the average from each signal to eliminate the dc component and decimate to emphasize the low frequency components using a down-sampling rate of 20. The Blackman-Harris window (with length of 5 sec) which has widest main lobe but smallest height of side lobes was used to smooth the periodogram and to minimize leakage. In this paper, we are just interested in the magnitude response of PSD.

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E-mail: bmoon@pdx.edu

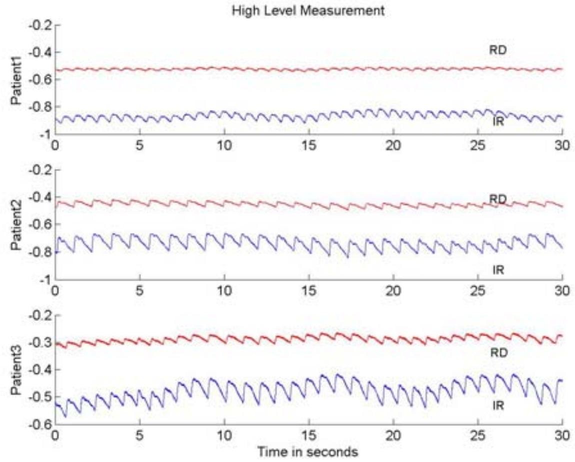

Figure 1. Red and Infrared signals at HLM for the duration of 30 sec

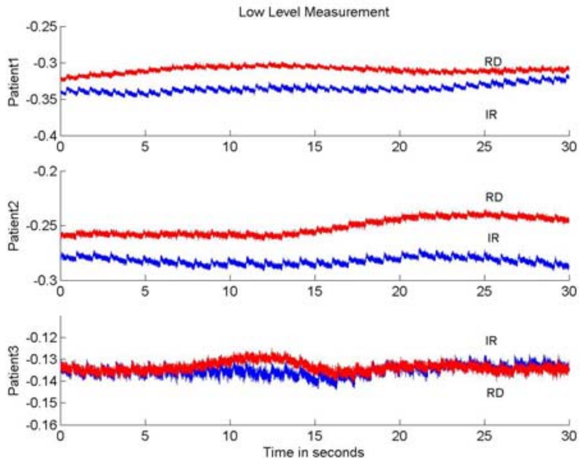

Figure 2. Red and Infrared signals at LLM for the duration of 30 sec

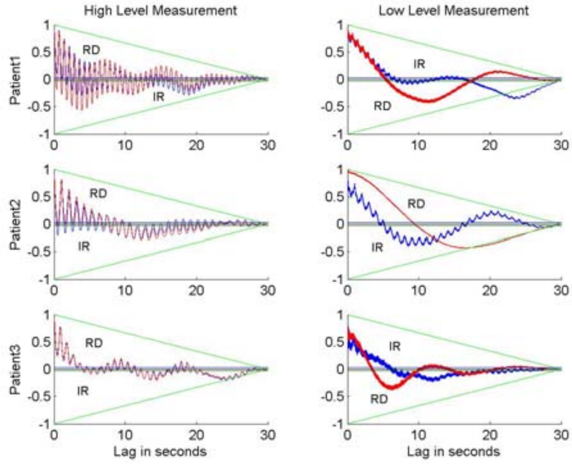

Figure 3. Autocorrelation Functions for both HLM and LLM

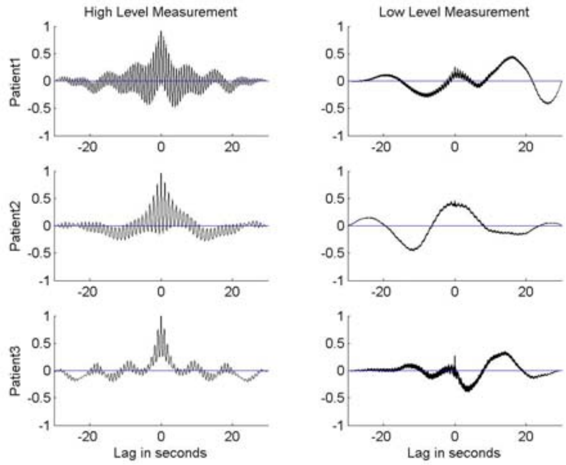

Figure 4. Crosscorrelation Functions for both HLM and LLM

The estimated coherency spectrum represents the correlation of red and infrared signals at each frequency. It is bounded from 0 to 1. The average of the signal was removed prior to the spectral Estimation. The Welch's method was used to calculate the spectral components and there was 50% overlap to reduce the variance of the estimator. This however causes increasing bias [3].

III. RESULTS

Three patients' red and infrared time series are shown in Figures 1 and 2. All harmonic components of the signals are driven by respiratory and cardiac components. All signals in the HLM show bigger amplitude and less noise compared to the LLM. The cardiac cycles were corrupted by noise but the respiratory components have been easily detected in the LLM. The strongest cardiac and respiratory cycles were seen in both Patient 3 measurements. The red signals have less amplitude due to more light absorption by the capillary tissue bed. It was hard to detect the second cardiac cycle in the LLM due to the noise. Plots for the ACF are shown with the confidence bands and bias lines in Figure 3. Due to the even symmetry, the plots show only positive portion of lag. All ACFs decreased asymptotically to the confidence band and converged to zero at the maximum lag. Additionally it can be observed that ACF for all patients shows lower values and do not exceed 0.5.

In the HLM, the ACFs of red and infrared signals overlapped and showed almost same shapes but in LLM they had a different phase.

Figure 4 shows the all CCFs from the -30 to 30 sec of lags. The CCFs show that the red and infrared signals are correlated each other. They converged to final lag and all CCFs in the HLM showed even symmetry; no symmetry was found in the LLM. An interesting result is we can still detect the strong oscillation due to cardiac component in the HLM but weak oscillation due to the respiratory component are shown in the LLM.

Figure 5 and 6 show the magnitude responses of the PSD that gave us a good visualization of cardiac and respiratory cycles. We could easily observe first and second cardiac component so as respiratory component in infrared PSD throughout all patients. For patient 1, the distinct first and second cardiac frequencies were at 1.2 Hz and 2.8 Hz. The patient showed the fastest heart rate compared to all other patients. The respiratory components of all patients were closely located near DC component. Respiratory components were shown at 0.15Hz in the PSDs. All plots of the PSD are scaled by multiplying 1000 to emphasize their magnitude values. The difference of magnitude of the PSD between red and infrared are not the same throughout the patients. But the fact that the magnitudes of the PSDs of infrared signals are much bigger than the red PSDs is the same. Figure 7 shows the magnified PSD of patient 3. The respiratory at 0.2 Hz and cardiac components at 1.2 and 2.2 Hz were easily detected.

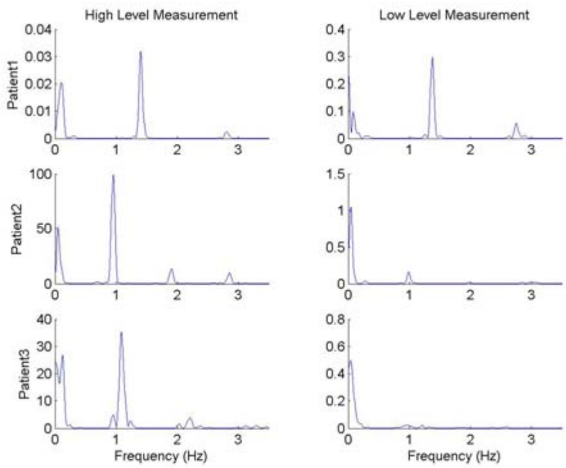

Figure 5. PSD of Infrared signals in the range of low frequency

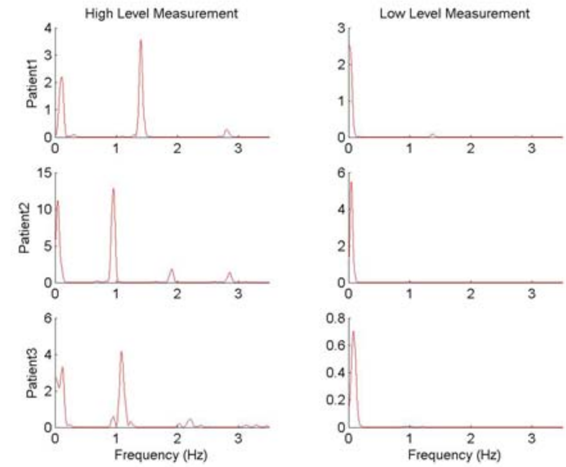

Figure 6. PSD of Red signals in the range of low frequency

In the PSD of red signals in the LLM on respiratory components are detected. An interesting result in the plot was that each cardiac cycle had side lobes. This phenomenon can be explained by using amplitude modulation; high frequency carrier (Cardiac cycles) modulated the information signal (respiratory components).

The results of Coherency estimation are illustrated in Figure 8. In real case, Coherency is hard to estimate because it is the ratio of two random variables. The Coherency spectra for the patients contained strong cardiac and respiratory components in the HLM. For example, Patient 3 showed the strongest respiratory component at 0.2 Hz compared to other patients but the second cardiac component was distorted. The Coherency spectrums for LLM were remarkably weak and the respiratory and cardiac components were hard to detect. This means there was no frequency correlation between red and infrared signals at LLM.

IV. Discussion

We assume that red and infrared signals are strongly correlated in the time and in the frequency domain. Pulse oximetry signals vary from patient to because patient's heart rate and respiratory cycles are different one another.

In the HLM, all of the results are consistent in measuring the oxygen saturation.

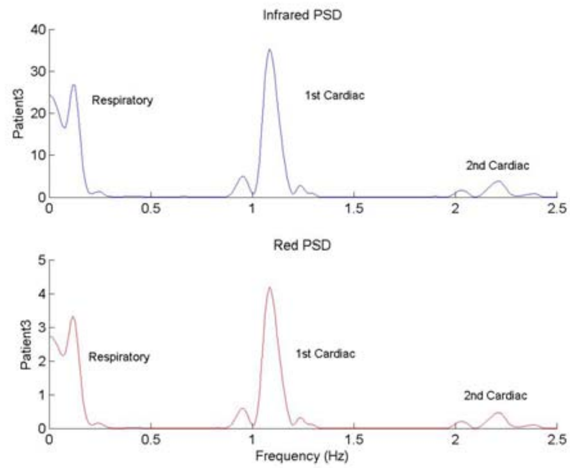

Figure 7. Magnified PSD of infrared and red signals for Patient 3

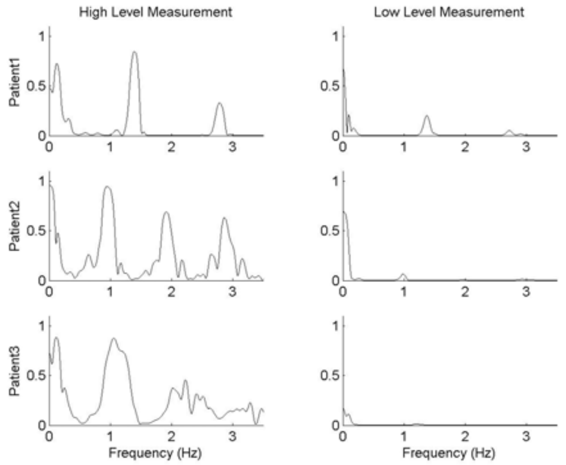

Figure 8. Coherency between red and infrared signals

We can observe the similar patterns such as the shape of the correlation function and Coherency. However in the LLM we can not detect any type of pattern. The respiratory components are dominant in LLM because the cardiac components are deformed and corrupted by noise**.** On the other hand, the cardiac components are dominant and distinguishable in the HLM. We realize that the patient's physiological condition such as blood pressure and arterial volume changes is varied due to the different height of measurements.

The PSD of the red signals in the LLM has very weak power and it was hard to detect the cardiac component. This implies that pulse oximetry may fail to read the oxygen saturation or give false alarms in the condition of the LLM: If there is no harmonic component of red signal, R value is close to zero. For that reason, the percentage of oxygen saturation may be over the 100.

The red light is absorbed by many other components, such as hemoglobin, bone, and tissue. The infrared light is only absorbed by oxy-hemoglobin. This means that more infrared light reaches to the photo-detector. Therefore, the PSD of infrared signals have bigger amplitudes.

V. Conclusion

We can confirm the consistent patterns of pulse oximetry signals from the limited experiment and see the fact that pulse oximetry may not be calibrated correctly or even fail to read the oxygen saturation.

Statistical Signal Processing techniques are powerful tools to analyze pulse oximetry signals, especially in the frequency domain. The sample consists of only 3 healthy patients. Due to this fact, more data is required to make proper conclusion. Further researches are required for the different condition of subject such as ill patient and for the different type of measurements.

References

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