# Stimulating Student Learning with a Novel "In-House" Pulse Oximeter Design

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## Abstract

This paper addresses the design of a plug-and-play pulse oximeter and its application to a biomedical instrumentation laboratory and other core Electrical Engineering courses. The low-cost, microcontroller-based unit utilizes two light-emitting diodes as excitation sources, acquires reflectance data with a photodiode, and sends these raw photo-plethysmographic data to a personal computer via an RS-232 serial link. A LabVIEW interface running on the personal computer processes these raw data and stores the results to a file. The design of this pulse oximeter is unique in two ways: the excitation sources are driven just hard enough to always keep the photodiode active (meaning the sensor can be used in ambient light), and the hardware separates out the derivatives of the red and infrared photo-plethysmograms so that it can amplify the pulsatile component of each signal to fill the range of the analog-to-digital converter. Unlike commercial pulse oximeters whose packaging hides the hardware configuration from the students, the open, unpackaged design stimulates student interest and encourages dialogue with the developer; the in-house nature of the design appeals to students. Moreover, most pulse oximeters on the market are expensive and provide users with a front panel that displays only percent oxygen saturation and heart rate. This low-cost unit provides unfiltered pulsatile data, allowing students to investigate tradeoffs between different oxygen saturation calculation methods, test different filtering approaches (e.g., for motion artifact reduction), and extract other biomedical parameters (e.g., respiration rate and biometric indicators). Time-domain data from these units have been used in linear systems and scientific computing courses to teach filtering techniques, illustrate discrete Fourier transform applications, introduce time-frequency principles, and test data fitting algorithms.

## I. Introduction

An optical pulse oximeter measures the intensity of light passing through heterogeneous tissue and uses variations in this light intensity (primarily resulting from the fractional volume variation of arterial blood) to calculate blood oxygen saturation. Due to its non-invasive nature, high precision in its operational range, and reasonable cost, optical pulse oximetry is widely adopted as a standard patient monitoring technique. Although its foundations date back more than fifty years,[1] many facets of this technology still attract researchers. Current interest areas include motion artifact reduction,[2, 3] power consumption optimization,[4] low-perfusion measurements,[5, 6] and issues germane to various application environments (e.g., wearability for battlefield and home care monitors).[7-9] It is important for biomedical engineering students to understand the principles of pulse oximetry, hardware/software design issues, and signal processing approaches.

Pulse oximeter design addresses engineering areas such as optical component selection, mechanical layout, circuit design, microprocessor control, digital communication, and signal processing. Therefore, a pulse oximeter not only serves as an excellent study vehicle that allows students to learn techniques such as photoplethysmographic signal processing; it also provides a platform where students can acquire hands-on experience in practical device design. In addition, the real-time data that a pulse oximeter offers gives instructors flexibility when assigning projects and homework to students of various educational levels (graduate and undergraduate) and backgrounds (e.g., electrical engineering or biology).

Many commercial pulse oximeters display calculated parameters (i.e., percent oxygen saturation and heart rate) on their front panels, hiding the original unfiltered data from which these calculations were made. In this paper, we present an "in-house" pulse oximeter that provides raw sensor data for use in the classroom. The device is utilized in bioinstrumentation laboratory sessions, and its data provide real-world signals to other core Electrical Engineering courses.

This paper first briefly describes the theory behind photoplethysmographic (PPG) pulse oximetry. It then presents the development of a pulse oximeter, emphasizing design features that enable its application to education. These features include (a) a stand-alone pulse oximeter module with a novel circuit design, an open form-factor, and multiple signal outputs, (b) a personal computer station with a flexible, user friendly LabVIEW interface and a variety of signal processing options, and (c) the production of raw data that can be used for parameter extraction exercises. The paper describes how this device and it features have been applied in classroom environments to stimulate student learning. Several examples are introduced in detail, including (a) a pulse oximetry laboratory/lecture pair for a bioinstrumentation course sequence, (b) data sources for course projects in Linear Systems (EECE 512) and Scientific Computing (EECE 840), and (c) a platform upon which undergraduate honors research students can build. This approach can be extended to other devices and classes.

## II. Theory – Principles of Pulse Oximetry

PPG pulse oximetry relies on the fractional change in light absorption due to arterial pulsations. In a typical configuration, light at two different wavelengths illuminating one side of tissue (e.g., a finger) will be detected on the same side (reflectance mode) or the opposing side (transmission mode) after traversing the vascular tissues between the source and the detector.[10] When a fingertip is simplified as a hemispherical volume that is a homogenous mixture of blood (arterial and venous) and tissue, the detected light intensity is described by the Beer-Lambert law: [11]

$$I_t = I_0 \left(e^{-\mu_{at}T}\right)\left(e^{-\mu_{av}V}\right)\left(e^{-\mu_{aa}A}\right) \quad (1)$$

where $I_0$ is the incident light intensity, $I_t$ is the light intensity detected by the photodetector, and $\mu_{at}$, $\mu_{av}$, and $\mu_{aa}$ are the absorption coefficients of the bloodless tissue layer, the venous blood layer, and the arterial blood layer, respectively, in units of $cm^{-1}$.

The heart's pumping action generates arterial pulsations that result in relative changes in arterial blood volume, represented by $dA$, which adds an "ac" component to the detected intensity:

$$dI_t = -I_0 \mu_{aa} \left(e^{-\mu_{at}T}\right)\left(e^{-\mu_{av}V}\right)\left(e^{-\mu_{aa}A}\right) dA \quad (2)$$

Multiple elements contribute to the attenuation of light traveling through tissue, and arterial pulsation has only a small relative effect on the amount of light detected (on the order of one percent or less; see Figure 1).

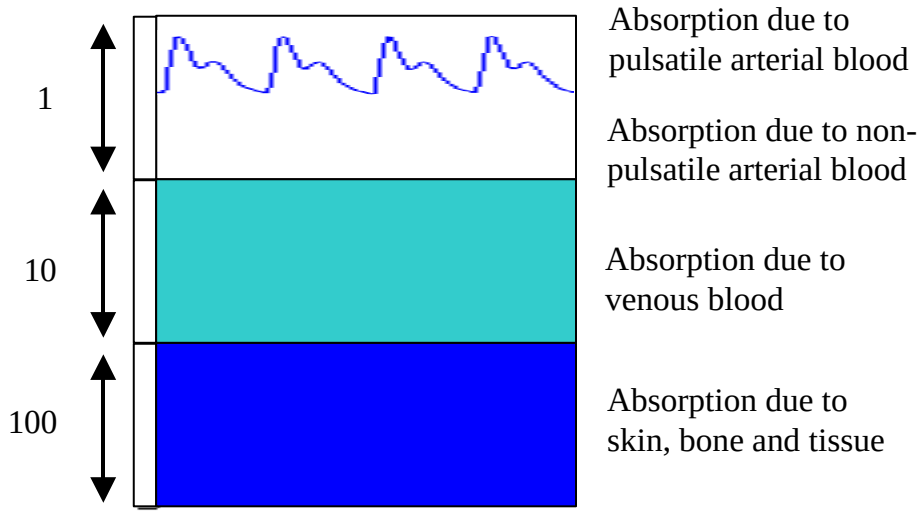



**Figure 1. Breakdown of the components in the detected photo-plethysmographic signal.[12]**

Dividing this change by the dc value normalizes this variation:

$$\frac{I_{ac}}{I_{dc}} = \frac{dI_t}{I_t} = -\mu_{aa} dA \tag{3}$$

The ratio of the above ratio for two wavelengths ('r' for red, 'IR' for infrared) is given by

$$R = \frac{(dI_t / I_t)_r}{(dI_t / I_t)_{IR}} = \frac{\mu_{a,r}}{\mu_{a,IR}}, \tag{4}$$

where $\mu_{a,i}$ can be expressed as a function of $S_aO_2$,[13] arterial oxygen saturation:

$$\mu_{a,i} = \frac{H}{v_i}\left[S_aO_2\sigma_a^{100\%} + (1 - S_aO_2)\sigma_a^{0\%}\right] \tag{5}$$

Here, $i = r, IR$, while $\sigma_a^{100\%}$ and $\sigma_a^{0\%}$ are the wavelength-dependent optical absorption cross sections of the red blood cells containing totally oxygenated and totally deoxygenated hemoglobin, respectively. One can therefore calculate arterial oxygen saturation using

$$S_aO_2 = \frac{R\sigma_{a,IR}^{0\%} - \sigma_{a,r}^{0\%}}{(\sigma_{a,r}^{100\%} - \sigma_{a,r}^{0\%}) + R(\sigma_{a,IR}^{0\%} - \sigma_{a,IR}^{100\%})} \tag{6}$$

Equation (6) provides the desired relationship between the experimentally-determined ratio *R* and the arterial oxygen saturation $S_aO_2$. Researchers assume this relationship applies to monochromatic light sources. In reality, commonly available LEDs are used as light sources and typically have spectral widths of 20 to 50 nm. Therefore, the standard molar absorption coefficient for hemoglobin cannot be used directly in (6). Furthermore, the simplified mathematical description above only approximates a real system that incorporates

inhomogeneities and mechanical movement. Consequently, (6) is often represented empirically by fitting clinical data to the following generalized function:

$$S_aO_2 = k_1R + k_2 \tag{7}$$

where, e.g., $k_1$= -25.6, $k_2$= 118.8[14] or $k_1$= -25, $k_2$= 110.[15]

## III. Methods

### *A. Pulse Oximeter Development*

As shown in the functional block diagram in Figure 2, a pulse oximeter consists of three main units: (1) an optical probe, (2) a circuit module that hosts an analog amplifier, signal conditioning element, and microcontroller, and (c) a personal computer that receives data from the circuit module and processes, displays, and stores these data.

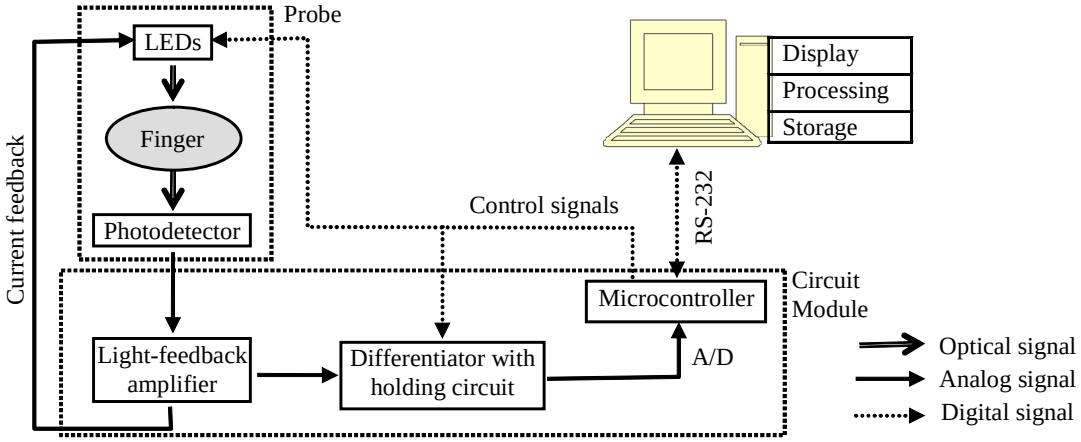



**Figure 2. Functional block diagram of the pulse oximeter.**

The analog portion of the pulse oximeter consists of a light-feedback amplifier and an analog differentiator with a specialized sample and hold circuit. The current feedback design adjusts the light level at the excitation LEDs such that the detected light intensity is constant, keeping the photodiode centered in its active region. To improve the stability of this feedback loop, a photodiode with smaller gain, rather than a phototransistor, is used as a photodetector. Two LEDs with wavelengths of 660 nm and 940 nm were selected as excitation sources.

As discussed earlier, the “ac” component resulting from arterial blood volume variation is very small. If A/D conversion is performed on the overall signal, this tiny “ac” component will be buried in the “huge” “dc” component after conversion. A differentiator addresses this issue. It removes the “dc” component by subtracting the previous signal voltage-level from the present signal voltage-level and amplifies this difference, yielding the “ac” component. A hold circuit is added to store voltage-levels from the previous sample cycle. The differentiator improves signal resolution by allowing one to take advantage of the full range of the A/D converter.

This circuitry is coordinated by a PIC microcontroller. Three output lines control the operation of the circuitry, and two A/D inputs sample the desired signal. Two outputs modulate the two light sources and switch the charging and discharging of their corresponding hold capacitors. The

other output operates the differentiator. The two A/D inputs acquire and digitize two signals: the "dc" signal when the differentiator is turned off (it is actually the original signal that includes both "dc" and "ac" components) and the amplified difference of the present and previous voltage level when the differentiator is turned on.

The PIC microcontroller also operates an RS-232 port to a personal computer running a LabVIEW interface. Digitized data are sent to the PC over this RS-232 interface. Because the sensor module and personal computer communicate asynchronously, and 8 bytes (two bytes for each signal) are sent in each RS-232 packet, a handshaking protocol is used to synchronize the two devices. The PC generates an acknowledgement after successfully receiving each data packet so that the pulse oximeter module can transmit the next data packet.

On the PC, LabVIEW virtual instruments (a) reconstruct the differentiated data, (b) filter the pulsatile signal with motion artifact reduction algorithms, (c) display the differentiated and reconstructed waveforms, (d) compute and display values for heart rate and blood oxygen saturation (see Figure 4), and (e) store the original and processed data to a text file for follow-up analysis. The data in the file are in columnar format:

Column 1 – Time in milliseconds,
Column 2 – $d(I_{ac})_{ir}/dt$ (derivative of the near-infrared signal)
Column 3 – $(I_{dc})_{ir}$
Column 4 – $d(I_{ac})_{red}/dt$ (derivative of the red signal)
Column 5 – $(I_{dc})_{red}$
Column 6 – $(I_{ac})_{ir}/dt$ (reconstructed near-infrared signal)
Column 7 – $(I_{dc})_{red}$ (reconstructed red signal)

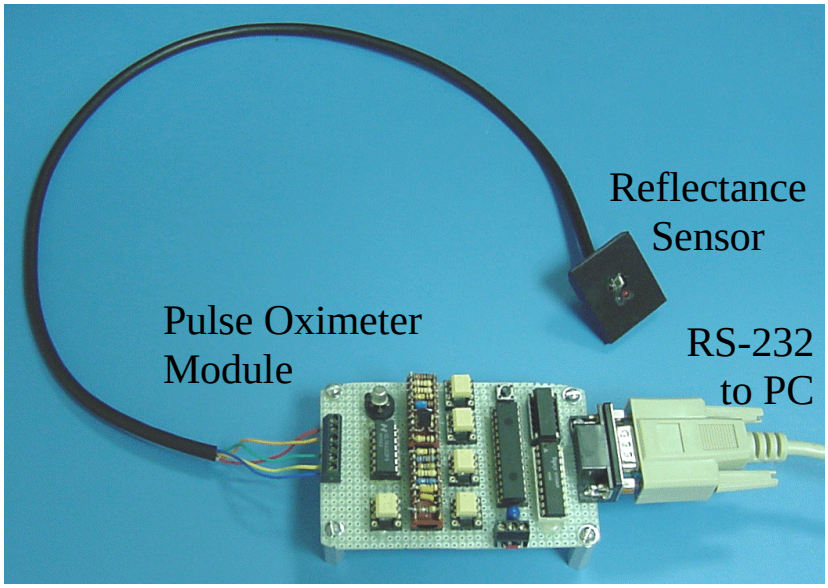



**Figure 3. Pulse oximeter module and reflectance probe.**

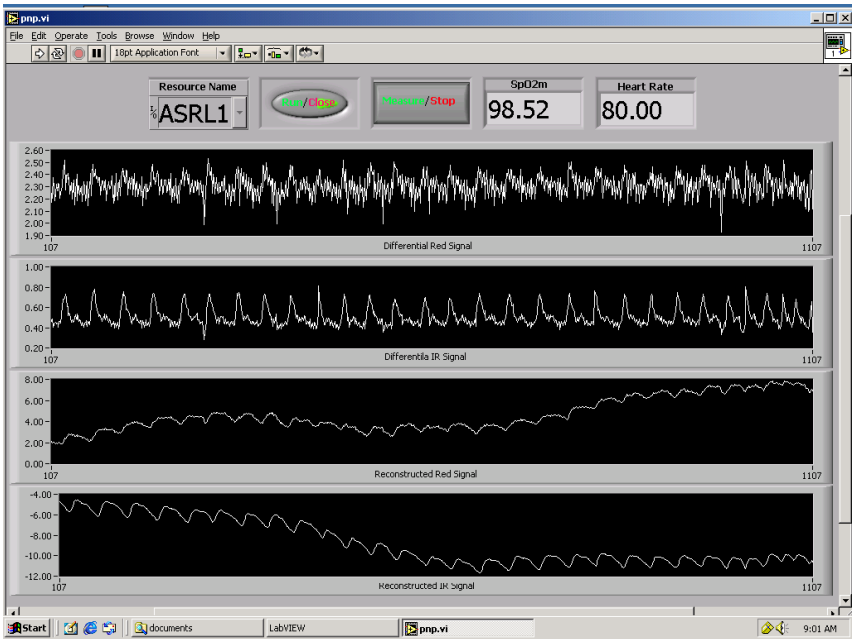



**Figure 4. LabVIEW virtual instrument for the pulse oximeter. In addition to heart rate and blood oxygen saturation (%), the interface displays the red and infrared derivative data (top two waveforms) and the red and infrared reconstructed data (bottom two waveforms).**

### *B. A Pulse Oximetry Lecture/Laboratory Pair*

At Kansas State University, the 4-credit-hour Bioinstrumentation course sequence (URL: http://www.eece.ksu.edu/~eece772/) consists of three courses instructed by faculty from the Department of Electrical & Computer Engineering (EECE) and the Department of Anatomy and Physiology (AP). These courses are EECE 772 (Theory and Techniques of Bioinstrumentation, 2 hours), EECE 773 (Bioinstrumentation Design Laboratory, 1 hour), and AP 773 (Bioinstrumentation Laboratory, 1 hour). These courses can be taken for either undergraduate or graduate credit. The two laboratory hours provide hands-on experience and are intended to help students obtain a deeper understanding of concepts learned in lectures.

The pulse oximeter discussed earlier serves as a basis for a lecture/laboratory pair in the Bioinstrumentation course sequence. In order to improve the quality of the laboratory, the second author designed a laboratory session for AP 773 that uses the pulse oximeter developed by the first author. Four sets of devices were constructed and have been used as teaching tools in these laboratory sessions. The **learning objectives** of this laboratory (i.e., what a student should be able to do upon completion of the laboratory) are the following:

- Explain the physiological origin of a photoplethysmogram
- Describe the hardware and software components required to determine blood oxygen saturation using light-based sensors
- Calculate blood oxygen saturation given a set of red/infrared plethysmograms
- Assess the character and spectral content of the time-varying signals

- Extract physiological data from a photoplethysmogram
- Describe person-to-person variations in plethysmographic signal data
- Calculate calibration coefficients using different approaches
- Counteract the effects of mild motion artifact

During the laboratory, the class is divided into groups of 2~3 students. Each group is equipped with a collection of components: a reflectance probe, a circuit module, a serial cable, and a personal computer with the LabVIEW interface installed. The students are first taught how to use the modules properly. They then gather PPG data from their team members at different body locations and save these data to files for later signal processing.

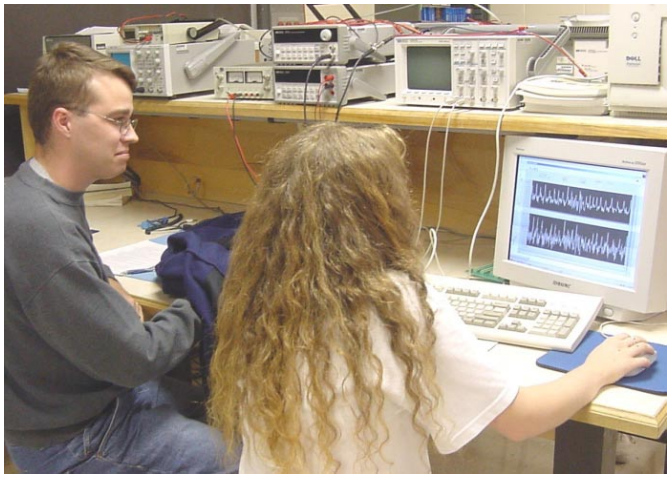


**Figure 5. Two students acquire photoplethysmographic data in the AP 773 pulse oximetry laboratory (Fall 2002).**

These data are processed using Microsoft Excel or MATLAB. In addition to observing and analyzing time domain data, the students are also required to interpret and understand the spectral components of the signal by performing Fast Fourier Transforms (FFTs) on the data sets. They implement different methods for calculating the "ac/dc" ratios required to obtain arterial oxygen saturation. Two calculation methods are used to compute these ratios. The methods correspond to Equations 3 and 4, which supply a parameter for Equation 7. The 'peak/valley' method considers the peak-to-valley amplitude of the reconstructed signal as $I_{ac}$ when calculating the "ac/dc" ratio. This method is evaluated with two different filtering techniques: a sliding average filter and a sliding median filter. The FFT method uses the spectral peaks of the red and near-infrared signals to represent $I_{ac}$ in the calculations. The students are then asked to compare the calculation methods and choose the best one.

Students are also encouraged to experiment with other noise reduction filters. Additionally, by observing and analyzing waveforms acquired from different team members, students can realize that factors such as skin color and perfusion affect the quality of acquired PPG data. They are also asked to evaluate the differences between PPG signals acquired at different body locations (e.g., wrist, forehead, or ear lobe) that have noticeably different vascular profiles.

### *C. Pulse Oximeter Applied to Other Educational Venues*

In addition to the lecture/laboratory pair noted in the previous section, the pulse oximeter design and the signal data gathered from various implementations of this design have been applied in multiple undergraduate (*EECE 499 – Honors Research*; *EECE 512 – Linear Systems*) and graduate (*EECE 840 – Scientific Computing*) educational venues. The **signals** acquired from this platform have been used in the following ways:

- data for time-domain smoothing algorithms (see Figure 6),
- signals for time- and frequency-domain filtering projects (see Figure 7 and Figure 8),
- waveforms for Fourier series reconstruction projects (see Figure 9), and
- signals for time-frequency spectrogram projects (see Figure 10).

The **modules** have also been used as starting points for various undergraduate honors research projects, as depicted in Figure 11.

**Course Projects.** In the smoothing exercises (see Figure 6), students are asked to perform signal processing exercises to 'smooth out' variations in signals corrupted with noise. Two of the common techniques are illustrated here. Polynomials, by their nature, are smooth curves whose numbers of peaks and valleys correspond to the order of the polynomial. In this figure, a polynomial of order 12 provides a reasonable representation of the original data set. Note that the behavior of the fitting polynomial is unpredictable outside of the original bounds. Sliding average and median filters are also a smoothing approach that can be implemented by a young student without much programming experience (the graph on the right in Figure 6 was produced with an Excel spreadsheet). For this photoplethysmograph (sampled at 160 Hz), a 7-wide sliding window appears to provide a reasonable job of smoothing out the noise while retaining the fundamental shape of the waveform.

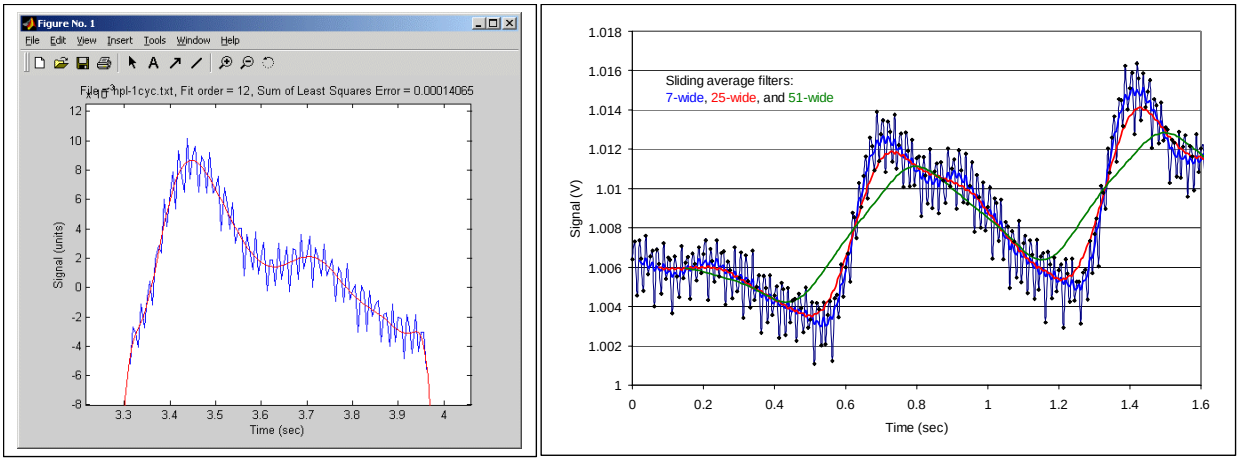



**Figure 6. Data smoothing algorithms (polynomial fits and sliding average filters) applied to photoplethysmographic data. These exercises were assigned in EECE 772 (Bioinstrumentation) and EECE 840 (Scientific Computing).**

In the EECE 512 project depicted in Figure 7, a student's code (1) loads a signal from an input ASCII text file, (2) performs a convolution (i.e., filtering operation) between the input signal and a cascade of 2nd-order Butterworth lowpass and highpass filters (which can be combined to create lowpass, highpass, or bandpass filters), (3) saves the output signal to disk, and (4) plots the original and filtered signals to the screen. Input signals for these simulations include both ideal

signals (e.g., pulses, square waves, and sinusoids) and real-world signals (e.g., biomedical signals such as electrocardiograms and light reflectance signals from the pulse oximeter modules presented here).

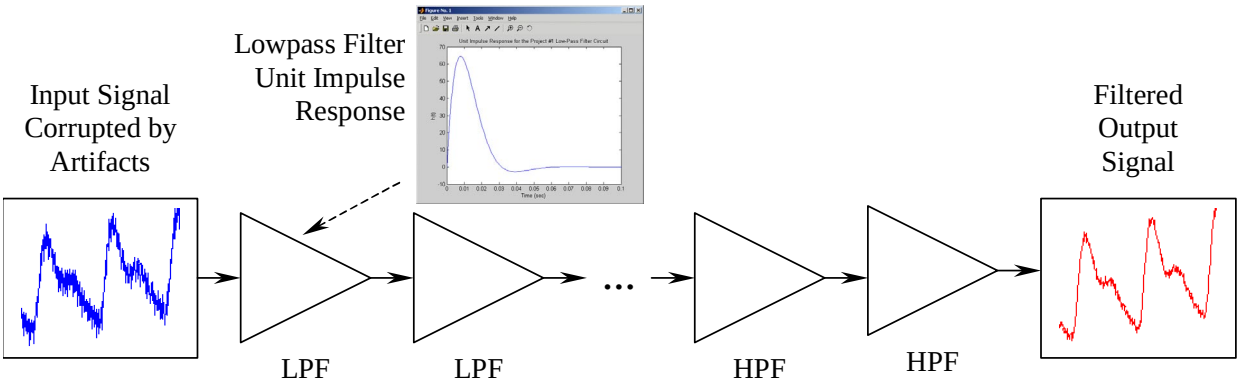



**Figure 7. Multi-stage filtering of photoplethysmographic data via time-domain convolution in EECE 512 (Linear Systems). Stages: 2nd-order lowpass and highpass filters.**

Frequency-domain filters are also an important part of a signals and systems course. In these projects, a student's program typically (1) loads an input signal from a file and calculates its Fourier transform, (2) calculates the frequency response of a filter chosen by the user, and (3) performs a frequency-domain filtering operation on the input signal: it multiplies the input signal spectrum by the spectrum of the filter and then takes the inverse Fourier transform of the result. The program then saves the input/output signals, their spectra, and the filter spectra to a set of ASCII text files and creates a plotting script that can be called by MATLAB or GNUPLOT. In the example illustrated in Figure 8, an ideal bandpass filter with a low cutoff of 0.3 Hz and a high cutoff or 15 Hz was used to remove the drift and 60 Hz noise present in the original plethysmographic signal.

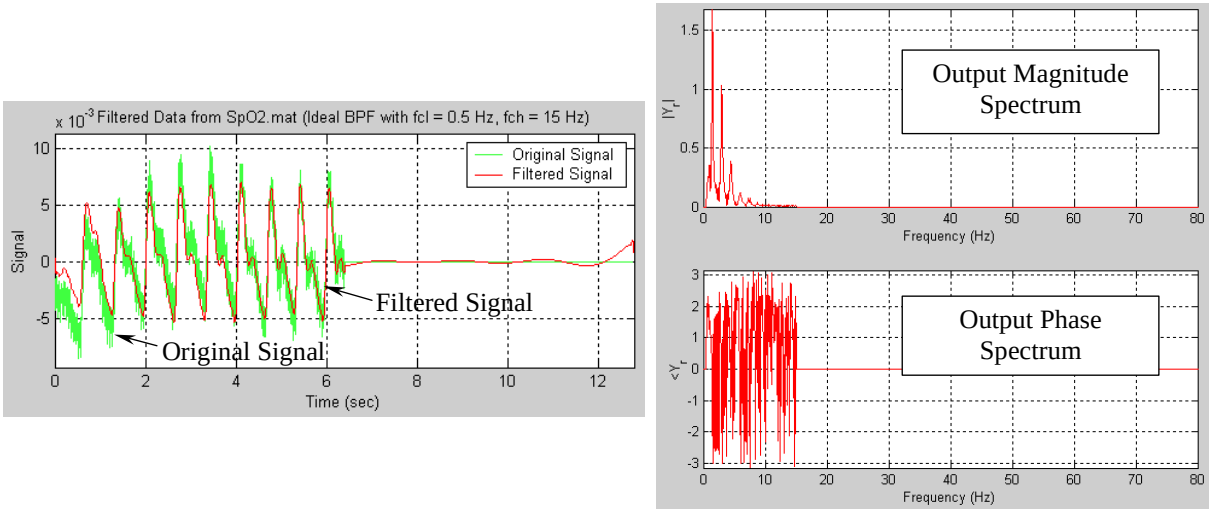
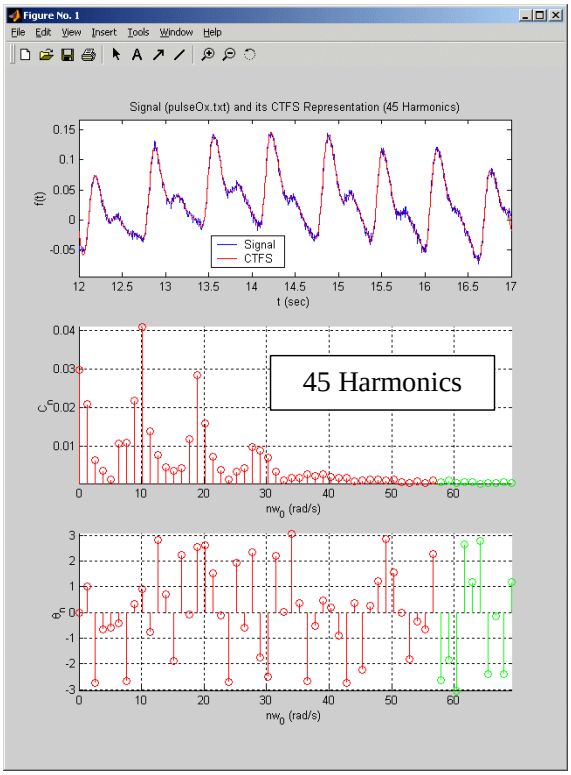



**Figure 8. Frequency-domain filtering of pulsatile light reflectance data to remove signal drift and 60 Hz noise. Course: EECE 512 (Linear Systems).**

Figure 9 illustrates the use of light reflectance signals in a Fourier series project. In the left part of Figure 9, the top set of axes displays a PPG signal and its Fourier series reconstruction. The middle and bottom axes plot the magnitude and phase coefficients, respectively, that were calculated for the reconstruction. Note that 45 harmonics (or cosines with different magnitudes and phases) were required to replicate the shape of the initial signal. In the canine electrocardiogram depicted on the right hand side of the figure, 125 harmonics produced a good reconstruction. This is due to the higher frequency components present in each QRS complex.

Human Pulse Plethysmogram




Canine Electrocardiogram

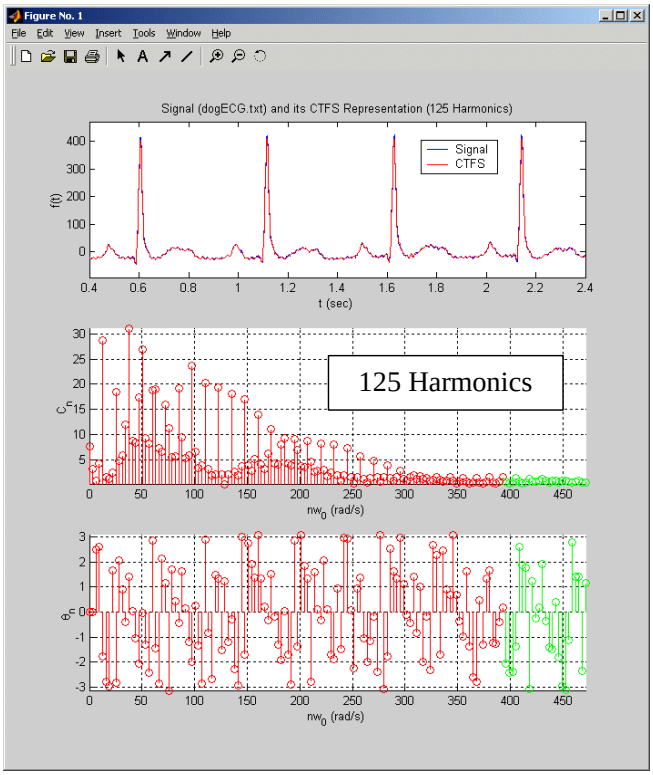



**Figure 9. Reconstruction of biomedical signal data (human finger photoplethysmogram and canine electrocardiogram) using Fourier series. Class: EECE 512 (Linear Systems).**

It can be helpful to understand how a signal's spectral character changes as a function of time. Figure 10 presents an example of a MATLAB interface that would be written by a student in a graduate scientific computing course. In this figure, the upper left set of axes plots the time-domain plethysmogram, while the lower left set of axes displays the spectrum of the signal versus time. The plots on the right depict the magnitude and phase spectrum of the input signal at the time denoted by the vertical line that occurs at ~55 seconds (see the upper left trace). The fields on the right side of the interface depict parameters that can be chosen by the user.

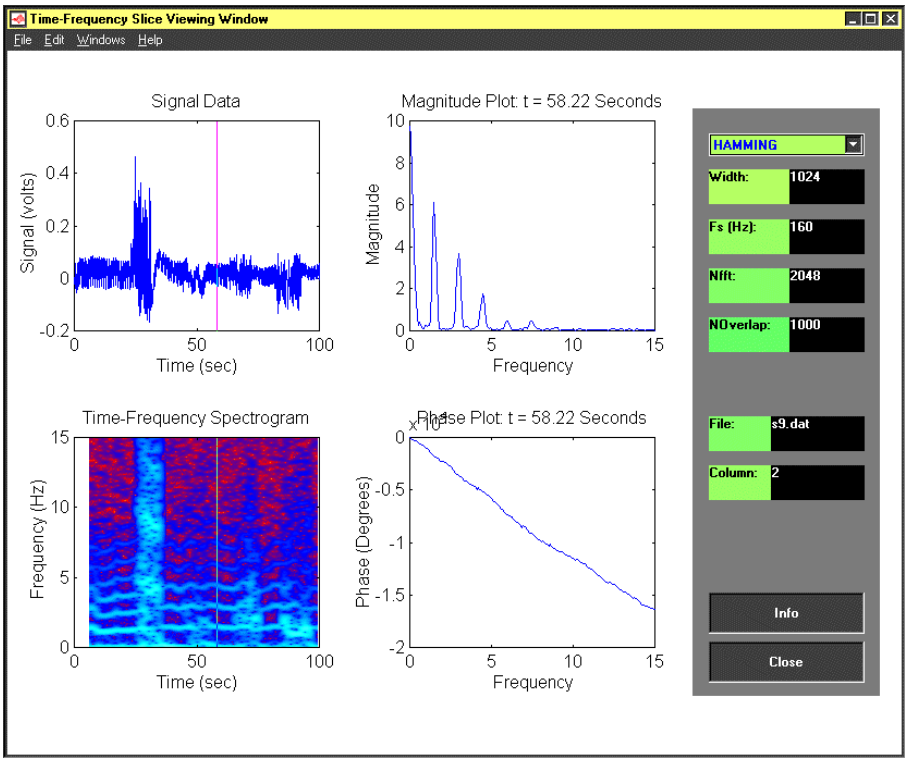


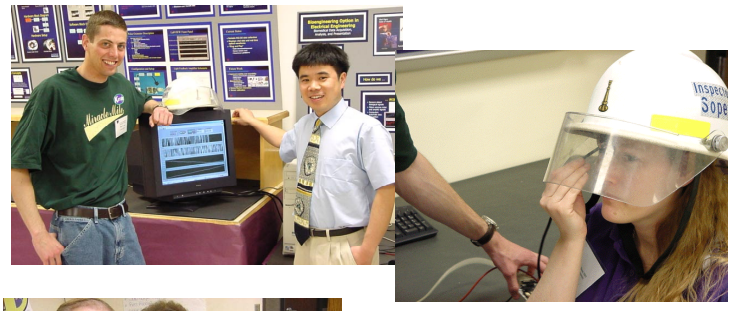

**Figure 10. Time-frequency analysis of reflectance data in EECE 840 (Scientific Computing).**

**Honors Research Projects.** The undergraduate Electrical & Computer Engineering curriculum at KSU allows high achieving students to perform research for course credit. The pulse oximeter modules presented in this paper have contributed to five EECE 499 (Honors Research) projects to date (see Figure 11). For the project shown at the top of the figure, Ben Young developed a system based upon the pulse oximeter module that acquired light reflectance data from the forehead using sensors mounted on a firefighter helmet. The goal of this project was to establish whether meaningful blood oxygen saturation measurements could be acquired continuously on an individual that needed to use their hands freely and could be exposed to dangerous levels of carbon monoxide. The second project from the top, managed by Shelly Allison and Craig Nelson, involved gathering light reflectance data from normal and hypertensive elderly subjects. These data will be analyzed for correlations between spectral behavior and the measured blood pressure of the subjects. The goal is to find a comfortable, noninvasive way to replicate the information normally provided by often painful blood pressure cuffs.

As noted in Figure 11, Jonathan Hicks investigated a method to use a patient's light reflectance data as a biometric indicator. This capability would allow a home monitoring system to authenticate the identity of a patient prior to uploading the patient's physiological data to a remote electronic patient record. The benefits of this approach are two-fold: (1) no interaction is required on the part of the patient and (2) the data are independently verified prior to submission. The plots in Figure 11 show a representative light reflectance signal for a patient and the single-period template used to represent that time-varying signal. Two other representative templates are also depicted in the figure to show how these wave shapes vary from person to person. This

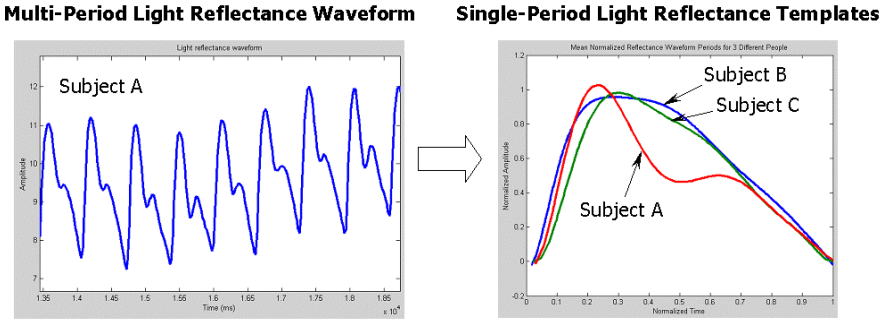
method uses a statistical test to determine whether a patient's current data are similar to the single-period template stored for the patient. Finally, Austin Wareing was supported by an NSF Research Experience for Undergraduates grant to optimize the light reflectance sensor design and improve the interaction between the pulse oximeter and the host LabVIEW program. His radial sensor design and a resulting set of waveforms are depicted at the bottom of Figure 11.

Ben Young: Forehead Measurements of Blood Oxygen Saturation for Use with Fire Fighter Helmets



Shelly Allison and Craig Nelson: Light-Based Indicators for Hypertension

Jonathan Hicks: Photoplethysmographic Signals as Biometric Authenticators




Austin Wareing: Optimization of Light Reflectance Sensors

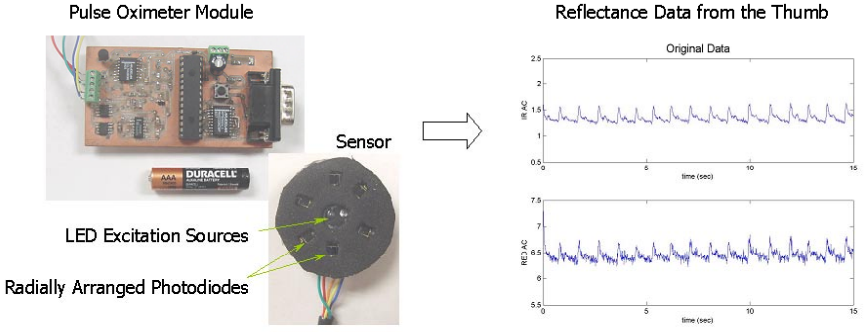



**Figure 11. Honors research projects that have benefited from the pulse oximeter design.**

## IV. Discussion and Conclusion

This paper presented initial efforts to apply an in-house pulse oximeter design to multiple secondary education venues. These efforts have indicated that students enjoy instructional experiences that utilize real-world devices, especially when they can manipulate elements of the design such as the signal processing algorithms that would normally be hidden from the user. The pulse oximeter modules have been used in four Fall offerings of the AP 773 laboratory (2001~2004). Because these home-grown pulse oximeters offer improved data access as compared to commercial products, instructors can experience far greater flexibility when assigning homework, which is especially appreciated when the background and educational experiences of the students vary significantly.

Each laboratory session that utilized these modules has been supported by device developers. Interactions between the device developers and the students (users) lead to experiences that are hard to replicate with packaged, off-the-shelf units. These interactions help the students appreciate the concepts discussed in lecture and allow them to become more familiar with the device development process.

As noted in the body of the paper, several other undergraduate and graduate courses have benefited from the data availability offered by these pulse oximeters. When asked, "What part of the project did you like the most" (on the survey for the Spring 2003 Linear Systems project depicted in Figure 7) one student responded, "Being able to see the ECG and pulse oximeter signals with the noise filtered out." Many other individuals in this class of 65 students had similar opinions about working with data provided by a device in a nearby laboratory. Processing real-world signals stimulated the students' interest the most, followed by the excitement of simply getting their code to work. The same Linear Systems student, when asked the question, "How could a project of this nature be improved?," responded with, "More realistic signals to filter − that is what made me feel like this was a realistic project."

The inexpensive hardware, plug-and-play features, and information-rich signals offered by these pulse oximeters have also provided starter platforms for honors students that wish to perform innovative research. These experiences not only help them to apply knowledge learned from their courses and understand recent developments; more importantly, they may also motivate these capable students to pursue careers in an expanding biomedical industry.

## Acknowledgements

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## References


[1] Brinkman, R. and W. G. Zijlstra. "Determination and continuous registration of the percentage oxygen saturation in clinical conditions," *Arch. Chir. Neurol.*, vol. 1, pp. 177-183.

[2] Swedlow, D. B. "Oximeter with motion detection for alarm modification," International Patent Application WO 94y22360 ~13, 1994, pp.

[3] Yao, J., and S. Warren. "A Novel Algorithm to Separate Motion Artifacts from the Photoplethysmographic Signal for a Pulse Oximeter," presented at 4th Joint EMBS-BMES Conf., San Francisco, CA, 2004.

[4] Rhee, Sokwoo, B.-H. Yang, and H. H. Asada,. "Artifact-resistant power-efficient design of finger-ring plethysmographic sensors," *IEEE Transactions on Biomedical Engineering*, vol. 48, May, pp. 795-805.

[5] Mannheimer, P.D., J.R. Cascini, M.E. Fein, and S.L. Nierlich. "Wavelength selection for low-saturation pulse oximetry," *IEEE Transactions on Biomedical Engineering*, vol. 44, March, pp. 148 - 158.

[6] Zonios, G., U. Shankar, and V.K. Iyer. "Pulse oximetry theory and calibration for low saturations," *IEEE Transactions on Biomedical Engineering*, vol. 51, May, pp. 818 - 822.

[7] Warren, S., J. Yao, and G. E., Barnes. "Wearable Sensors and Component-Based Design for Home Health Care," presented at 2nd Joint EMBS-BMES Conf., Houston, TX, 2002.

[8] Johnston, W.S., P.C. Branche, C.J. Pujary, and Y. Mendelson. "Effects of motion artifacts on helmet-mounted pulse oximeter sensors," presented at Proceedings of the IEEE 30th Annual Northeast Bioengineering Conference, 2004, 2004.

[9] Crilly, P.B., E.T. Arakawa, D.L. Hedden, and T.L. Ferrell. "An integrated pulse oximeter system for telemedicine applications," presented at Proceedings of the IEEE Instrumentation and Measurement Technology Conference, 1997, 1997.

[10] Bronzino, Joseph D. *IEEE Biomedical Engineering Handbook*: CRC Press, IEEE Press, 1995, 0-8493-8346-3.

[11] Yoshiya, Y. Shimada, and K. Tanaka. "Spectrophotometric monitoring of arterial oxygen saturation in the fingertip," *Med. Biol. Eng. Comput.*, vol. 18, pp. 27-32.

[12] Peck, Y., S. Cheang, and Peter R Smith. "An Overview of Non-Contact Photoplethysmography," *Electronic systems and control division research*, pp. 53~59.

[13] Schmitt, J. M. "Simple photon diffusion analysis of the effects of multiple scattering on pulse oximetry," *IEEE Transaction on Biomedical Engineering*, vol. 38, December, pp. 1194-1203.

[14] Mendelson, Yitzak, Peter W. Cheung, Michael R. Neuman, David G. Fleming, and Stephan D. Cahn. "Spectrophotometric Investigation of Pulsatile Blood Flow for Transcutaneous Reflection Oximetry," *Advances in Experimental Medicine and Biology*, vol. 159, pp. 93-102.

[15] Love, Jerry T., S. Warren, G. R. Laguna , and T. J. Miller. " Personal Status Monitor," Sandia National Lab SAND97-0418, 1997.


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